SEVENTH ANNUAL CARNEGIE MELLON CONFERENCE ON THE ELECTRICITY INDUSTRY 2011

CONFERENCE THEME: EMERGING PHENOMENA IN THE CHANGING ELECTRIC ENERGY INDUSTRY

POSTER SESSION

POSTER LIST

1.Competitive Equilibria for Stochastic Dynamic Markets: The Integration of Wind Power
Presenter: Gui Wang (guiwang2@illinois.edu)
Advisor: Prof. Sean Meyn (meyn@illinois.edu)
Department of Electrical and Computer Engineering and the Coordinated Science Laboratory
University of Illinois at Urbana-Champaign

2.Adaptive Robust Optimization for Security Constrained Unit Commitment Problems
Authors: Dimitris Bertsimas, Eugene Litvinov, Andy Sun, Jingye Zhao and Tongxin Zheng
Presenter: Andy Sun (sunx@mit.edu)
Advisor: Prof. Dimitris Bertsimas (dbertsim@mit.edu)
Operations Research Center, Alfred P. Sloan School of Management
Massachusetts Institute of Technology

3.Residential Electricity Disaggregation - Tailored Consumption Feedback in Smart Grids
Presenter: Markus Weiss (weissm@mit.edu)
Advisor: Prof. Richard C. Larson (rclarson@mit.edu)
Engineering Systems Division
Massachusetts Institute of Technology

4.Various Power System Impacts of the Large Scale Adoption of Electric Vehicles
Presenter: Remco Verzijlbergh (R.A.Verzijlbergh@tudelft.nl)
Advisor: Prof. Marija Ilić (milic@ece.cmu.edu)
Faculty of Technology, Policy and Management
Delft University of Technology

5.Control of a Liquid Fluoride Thorium Reactor with Biogeography-Based Optimization
Presenters:Rick Rarick (rrarick_mathematikos@roadrunner.com)
Mehmet Ergezer (mehmet.ergezer@gmail.com)
Looja Ratna Tuladhar (tuladharlooja@hotmail.com)
Advisors: Prof. Dan Simon (d.j.simon@csuohio.edu)
Prof. Charles Alexander (C.K.ALEXANDER@csuohio.edu)
Prof. F. Eugenio Villaseca (f.villaseca@gmail.com)
Department of Electrical and Computer Engineering
Cleveland State University

6.A Review of the Focus Areas for the Integration of Distributed Energy Resources (DER) to the Grid
Presenter: Akhilesh Magal (apmagal@cmu.edu)
Advisor: Prof. Mario Bergés (marioberges@cmu.edu)
Environmental Engineering - Green Design
Carnegie Mellon University

7.Equity and Efficiency in Residential Electricity Pricing
Presenter: Shira Horowitz (shira@cmu.edu)
Advisor: Prof. Lester Lave (lave@cmu.edu)
Carnegie Mellon Electricity Industry Center
Carnegie Mellon University

8.Added Value of Distributed Generation to Electric Energy Systems
Presenter: Masoud H. Nazari (mhonarva@andrew.cmu.edu)
Advisor: Prof. Marija Ilić (milic@ece.cmu.edu)
Department of Engineering and Public Policy
Carnegie Mellon University

9.Can a Wind Farm with Storage Compete in the Day-ahead Market?
Presenter: Brandon Mauch (bmauch@andrew.cmu.edu)
Advisors: Prof. Jay Apt (apt@cmu.edu)
Prof. Pedro Carvalho (pcarvalho@ist.utl.pt)
Department of Engineering and Public Policy
Carnegie Mellon University

10.Wind Speed Decomposition Modeling using Fourier Transform and Markov Process
Presenter: Noha Abdel-Karim (nabdelga@andrew.cmu.edu)
Advisor: Prof. Marija Ilić (milic@ece.cmu.edu)
Department of Engineering and Public Policy
Carnegie Mellon University

11.Adaptive Load Management (ALM) Including Risk Management of Load Serving Entities
Presenter: Jhi-Young Joo (jjoo@ece.cmu.edu)
Advisor: Prof. Marija Ilić (milic@ece.cmu.edu)
Department of Electrical and Computer Engineering
Carnegie Mellon University

12.Managing Bilateral Transactions in the Electricity Market
Presenter: Sanja Cvijić (sanja13@andrew.cmu.edu)
Advisor: Prof. Marija Ilić (milic@ece.cmu.edu)
Department of Electrical and Computer Engineering
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13.Energy Based Nonlinear FACTS Control
Presenter: Milos Cvetković (mcvetkov@andrew.cmu.edu)
Advisor: Prof. Marija Ilić (milic@ece.cmu.edu)
Department of Electrical and Computer Engineering
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14.Towards Distributed Calculation of Equilibria in Electric Power Systems
Presenter: Andrew Hsu (andrewhsu@cmu.edu)
Advisor: Prof. Marija Ilić (milic@ece.cmu.edu)
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15.Automatic Generation and Demand Control (AGDC)
Presenter: Nipun Popli (nipun@cmu.edu)
Advisor: Prof. Marija Ilić (milic@ece.cmu.edu)
Department of Electrical and Computer Engineering
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16.Distributed Control for Electric Power Systems to Enable the Integration of Renewable Energy Sources
Presenter: Kyri Baker (kabaker@andrew.cmu.edu)
Advisors: Prof. Gabriela Hug (ghug@ece.cmu.edu)
Prof. Xin Li (xinli@ece.cmu.edu)
Department of Electrical and Computer Engineering
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17.Optimal Usage of Transmission Capacity with FACTS Devices to Enable Wind Power Integration
Presenter: Rui Yang (ruiy@andrew.cmu.edu)
Advisor: Prof. Gabriela Hug (ghug@ece.cmu.edu)
Department of Electrical and Computer Engineering
Carnegie Mellon University

18.Real-Time Control of Energy Storage Devices in Future Electric Power Systems
Presenter: Dinghuan Zhu (dinghuan@cmu.edu)
Advisor: Prof. Gabriela Hug (ghug@ece.cmu.edu)
Department of Electrical and Computer Engineering
Carnegie Mellon University

19.A Monte Carlo Framework for Probabilistic Distribution Power Flow
Presenter: Tao Cui (tcui@andrew.cmu.edu)
Advisor: Prof. Franz Franchetti (franzf@ece.cmu.edu)
Department of Electrical and Computer Engineering
Carnegie Mellon University

20.Robust State-Estimation Procedure using a Least Trimmed Squares Pre-processor
Authors: Yang Weng, Rohit Negi, Zhijian Liu and Marija Ilić
Presenter: Yang Weng (yangweng@andrew.cmu.edu)
Advisors: Prof. Rohit Negi (negi@ece.cmu.edu)
Prof. Marija Ilić (milic@ece.cmu.edu)
Department of Electrical and Computer Engineering
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21.Greedy PMU Placement Algorithms for Power System State Estimation
Authors: Qiao Li, Rohit Negi, and Marija Ilić
Presenter: Qiao Li (qiaoli@cmu.edu)
Advisor: Prof. Rohit Negi (negi@ece.cmu.edu)
Department of Electrical and Computer Engineering
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Competitive Equilibria for Stochastic Dynamic Markets: the Integration of Wind Power*

Gui Wang

Department of Electrical and Computer Engineering, University of Illinois at Urbana-Champaign

Background

- Aggressive renewable energy target and smart grid vision
- Increased volatility and uncertainty of the power system
- Market environment driven by private interests
- Tightly coupled market and physical system
- Exotic behavior of electricity markets

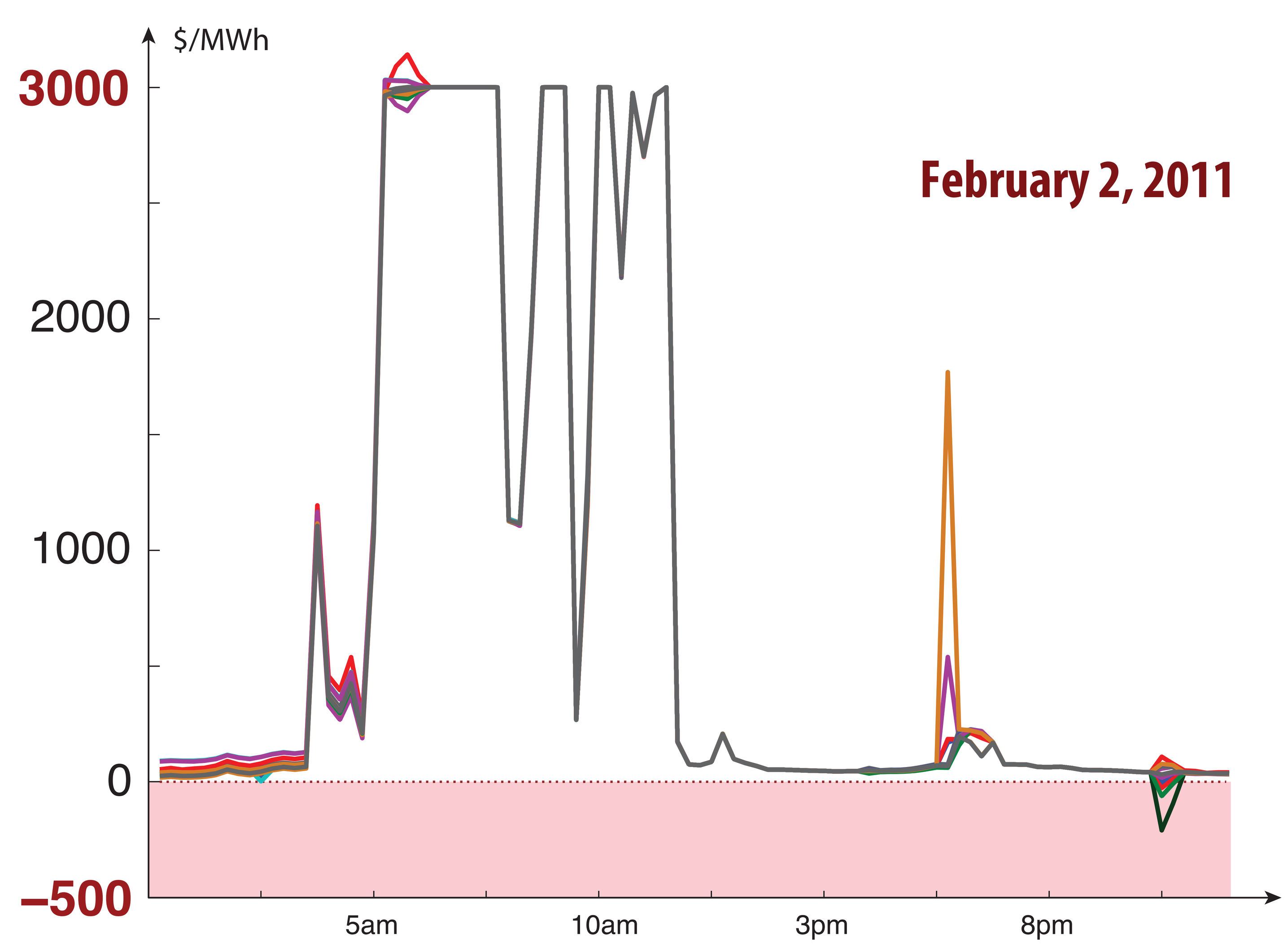


Fig.1: Prices in ERCOT Feb, 2, 2011

Goals

- Understand the impacts of volatile wind power on the economics and operation of power systems
- Investigate the interactions between system dynamics and market dynamics
- Provide insights on the integration of renewables and smart grid devices that can potentially inject volatile and uncertain patterns into the system

Model

- Continuous time real-time markets, possibly coupled with day-ahead or forward markets
- Uncertainties in supply/demand and operational constraints of the physical system are explicitly considered
- Price manipulation is excluded
- Externalities are disregarded
- All available wind generation is dispatched

Results

- Under some general conditions, equilibrium prices equal marginal costs, but only on average
- Price spikes are natural outcomes of stochastic markets with dynamic constraints
- When volatility is low, the consumer sees increasing benefit with additional wind generation
- Consumer welfare may fall dramatically as more and more wind generation is dispatched. With high volatility the consumer may be better served by reducing the wind power injected into the system

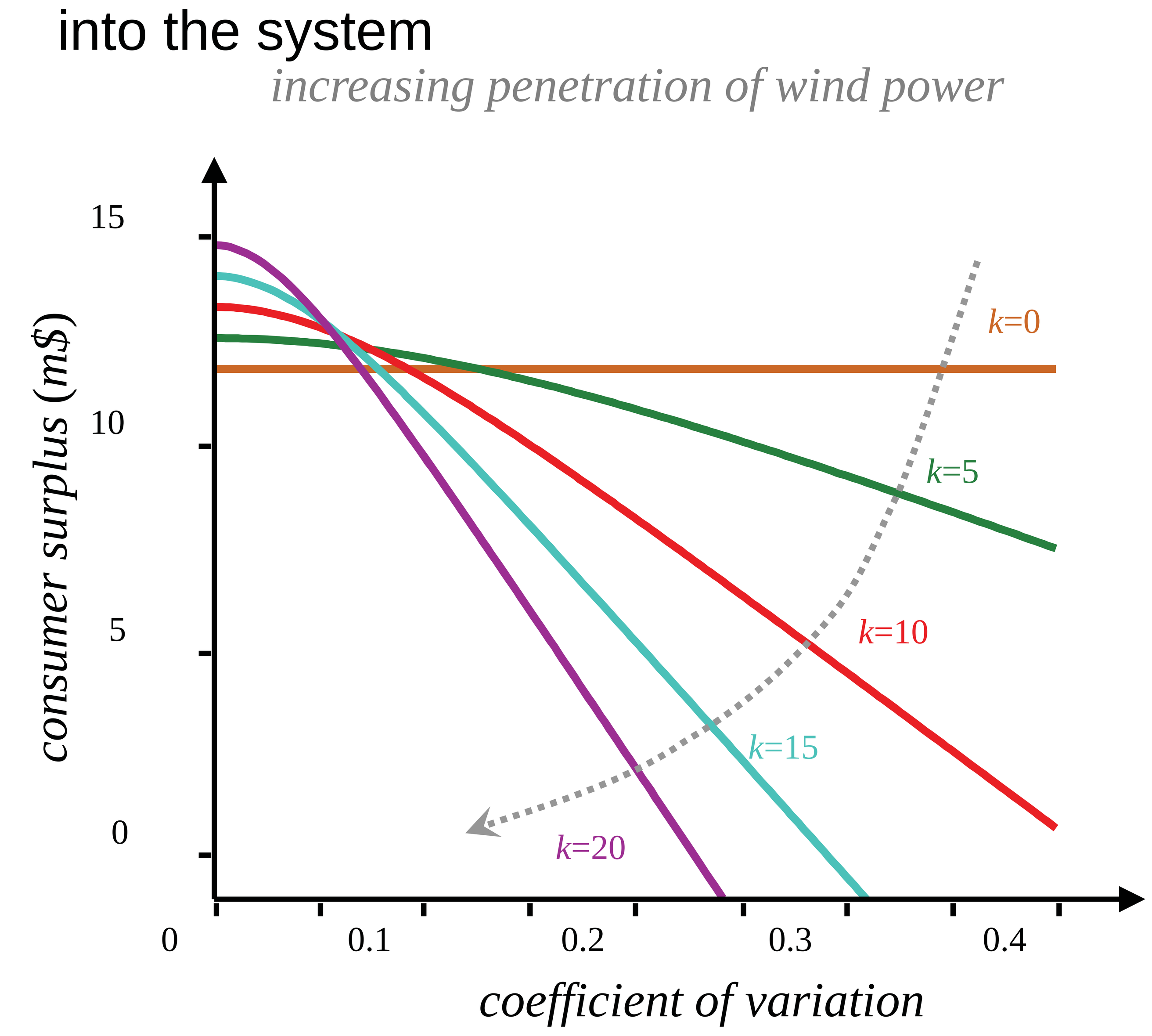


Fig.2: Consumer welfare w.r.t. wind penetration and volatility for a stylized market

Conclusions

- The dynamical characteristics of the efficient equilibria can be highly undesirable for consumers, suppliers, or both
- Benefits of wind generation may be offset by the impacts associated with volatility
- “Take all the wind” integration policy should be reconsidered

* *Joint work with Sean Meyn, Matias Negrete-Pincetic, Anupama Kowli, and Ehsan Shafieepoorfard*

G. Wang, A. Kowli, M. Negrete-Pincetic, E. Shafieepoorfard, and S. Meyn. *A Control Theorist's Perspective on Dynamic Competitive Equilibria in Electricity Markets*, 18th IFAC World Congress, 2011

S. Meyn, M. Negrete-Pincetic, G. Wang, A. Kowli, and E. Shafieepoorfard. *The Value of Volatile Resources in Electricity Markets*, Proc. of the 49th IEEE CDC, 2010

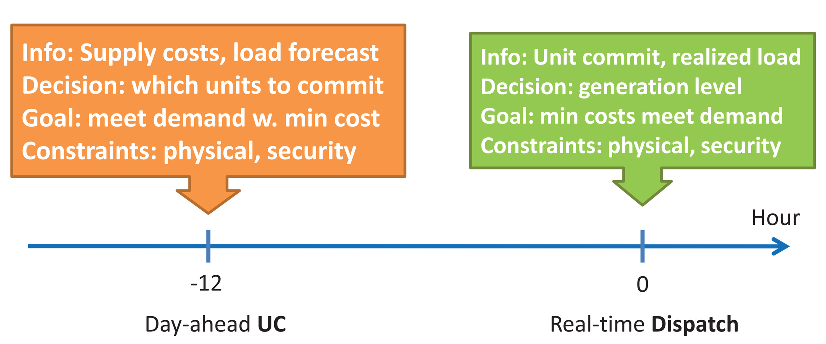
Adaptive Robust Optimization for Security Constrained Unit Commitment Problems

Xu Andy Sun
Operations Research Center, MIT
Joint work with Dimitris Bertsimas (MIT), Eugene Litvinov, Jinye Zhao, Tongxin Zheng (ISO-NE)

7th Carnegie Mellon Conference on Electricity Industry

Electric Power System Operations

- Day-Ahead Decision Making: Unit Commitment
  - Generators must be committed before real-time operation (long startup time)

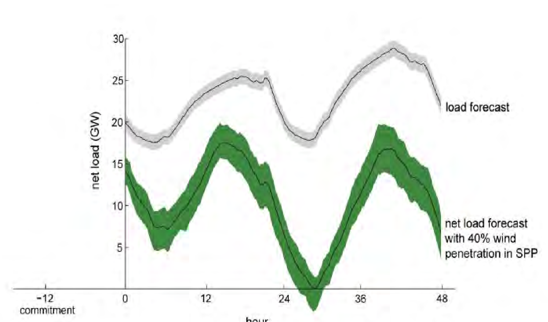


1

New Challenges: Growing Uncertainty

- New challenges

Supply Variation: Wind Power Penetration 40% annual growth



[Ruiz, Philbrick 10]

Load Variation: Demand Response Smart Grid Technology

Net Load Uncertainty Can be Huge!

2

Current Practice and Stochastic Optim.

- Reserve adjustment approach
  Incorporating extra reserve according to forecast

Drawbacks:
1. Uncertainty not explicitly modeled
2. Both system and locational requirement are preset, heuristic, ad hoc
3. Transmission constraint is not explicitly considered in designing requirement

- Stochastic optimization approach
  Uncertainty modeled by distributions and scenarios

Weakness:
Hard to select "right" scenarios in large systems
1. Large number of scenarios results in heavy computation

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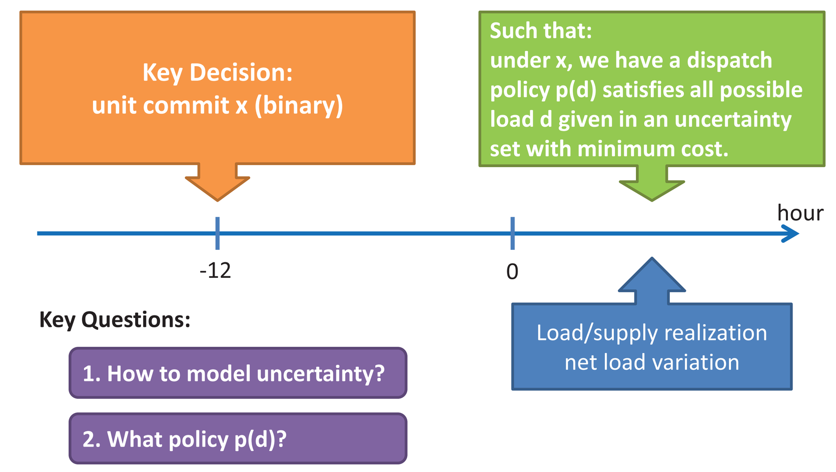
Our Proposal: Adaptive Robust Optimization

- Two-stage robust optimization framework



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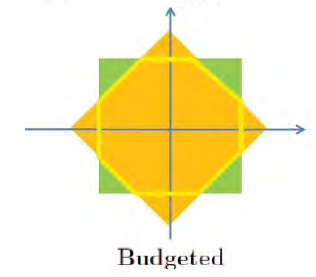
Model of Uncertainty

- Uncertainty model of net load variation

$$\mathcal{D}^t(\bar{\mathbf{d}}^t,\hat{\mathbf{d}}^t,\Delta^t) := \left\{ \mathbf{d}^t \in \mathbb{R}^{N_d} : \sum_{i\in N_d} \frac{|d_i^t - \bar{d}_i^t|}{\hat{d}_i^t} \le \Delta^t, \quad d_i^t \in [\bar{d}_i^t - \hat{d}_i^t, \bar{d}_i^t + \hat{d}_i^t], \forall i \in N_d \right\}$$

1. Total dev not too large
1. Correlation between different resources



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Decision Policy: Fully Adaptability

Dispatch solution fully adaptive to the uncertainty: $p_i^t(\mathbf{d}^t): \mathcal{D} \to \mathbb{R}_+$

$$\min_{\mathbf{x},\mathbf{u},\mathbf{v},\mathbf{p}(\cdot)} \sum_t \sum_i F_i^t x_i^t + S_i^t u_i^t + G_i^t v_i^t + \max_{\mathbf{d}\in\mathcal{D}} \sum_t \sum_i C_i^t p_i^t(\mathbf{d}^t)$$

Subject to:
- Commitment constraints: min-up/down times
- Dispatch constraints:
  - Energy balance
  - Production bounds
  - Ramp up/down
  - Flow limits

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Two-stage Adaptive Robust UC Problem

- The fully adaptive policy:
  - Objective: Fixed-Cost + Worst case Dispatch Cost

$$\min_{\mathbf{x},\mathbf{u},\mathbf{v}} \sum_t \sum_i F_i^t x_i^t + S_i^t u_i^t + G_i^t v_i^t + \max_{\mathbf{d}\in\mathcal{D}} \min_{\mathbf{p}\in W(\mathbf{x},\mathbf{d})} \sum_t \sum_i C_i^t p_i^t$$

s.t. $F(\mathbf{x},\mathbf{u},\mathbf{v}) \le 0$
$\mathbf{x},\mathbf{u},\mathbf{v}$ binary.

Find worst case d for dispatch

For a fixed x, d minimize dispatch cost

Constraints on commitment decision: Startup/shutdown, Min-up/down...

Second-Stage Problem

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Fully Adaptive Policy: Overall Algorithm

- Initialization: Get feasible x_0, solve $R(x_0)$ for dual var. $U=+\infty, L=-\infty$.
- Iteration k:
  - Step 1: $\min_{x,\alpha} c^T x + \alpha$
    s.t. $\alpha \ge \lambda_l^T D d_l + \rho_l^T M x + \pi_l^T r + v_l^T (B d_l + f), \forall l \le k,$
    $x \in X.$
    Let (x_k, α_k) be the optimum. $L = c^T x_k + \alpha_k$.
  - Step 2: Solve $R(x_k)$ to generate cuts
    $U = c^T x_k + R(x_k)$.
    If U-L small enough, stop and return x_k
    otherwise k=k+1

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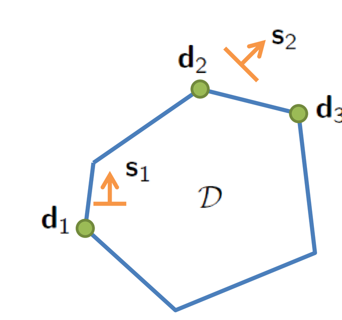
Solving 2nd -Stage Problem: Simple Gradient Algorithm

- Observation: optimal (d*,p*) are extreme points of D and W
- Algorithm sketch:
  - Fix **d**, solve dispatch, dual var gives gradient direction **s'd**
  - Maximize **s'd** over uncertainty set, find a new **d**, iterate.



1. Provable convergence to local minimum
2. In practice, converges fast (2-3 iter), consistent (from different starting points)

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Solving 2nd -Stage Problem: Outer Approximation

- Linearization of the bilinear term **s'd**:
  $L_k(\mathbf{d},\mathbf{s}) = \mathbf{s}_k^T \mathbf{d}_k + (\mathbf{s}-\mathbf{s}_k)^T \mathbf{d}_k + (\mathbf{d}-\mathbf{d}_k)^T \mathbf{s}_k$
- Algorithm sketch:
  - Fix d, solve dispatch, dual var q
  - Solve linearized problem:

$$\begin{aligned} &\max\ \beta + \rho^T M x + \pi^T r + v^T f \\ &\beta \le L_j(\lambda_j, v_j, d_j), \forall j = 1,\dots,k \\ &\lambda^T E + \rho^T R + \pi^T N + v^T A = c^T, \\ &Hd \le \Delta, \underline{d} \le d \le \bar{d}, \\ &\rho,\pi,v \ge 0, \lambda \text{ free.} \end{aligned}$$

1. Provable convergence to local minimum
2. In practice converges fast, consistent

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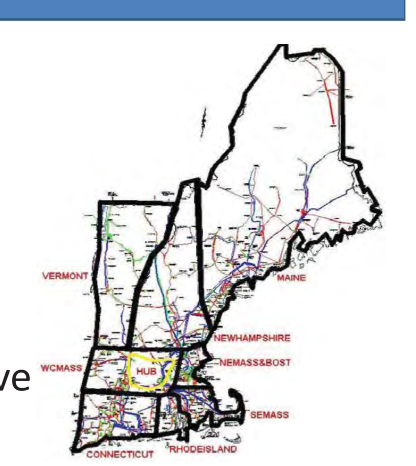
A Real-World Example: ISO-NE Power System

- 312 Generators
- 174 Loads
- 2816 Nodes
- 4 representative trans lines
- 24-hr data: gen/load/reserve
- Total gen cap: 31.4GW
- Total forecast load: 14.1GW



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Computation Procedure

- Solve AdptRob and ResAdj UC solutions for Δ^t = 0,0.1,…,1 for all t
- Fix UC solutions, simulate dispatch over load samples
  - 1000 load samples from $[\bar{d}_i^t - \hat{d}_i^t, \bar{d}_i^t + \hat{d}_i^t]$
- Compute average dispatch cost and std

- Avg dispatch cost: Economic efficiency
- Standard deviation: Price and Operation Stability
- Robustness to distributions

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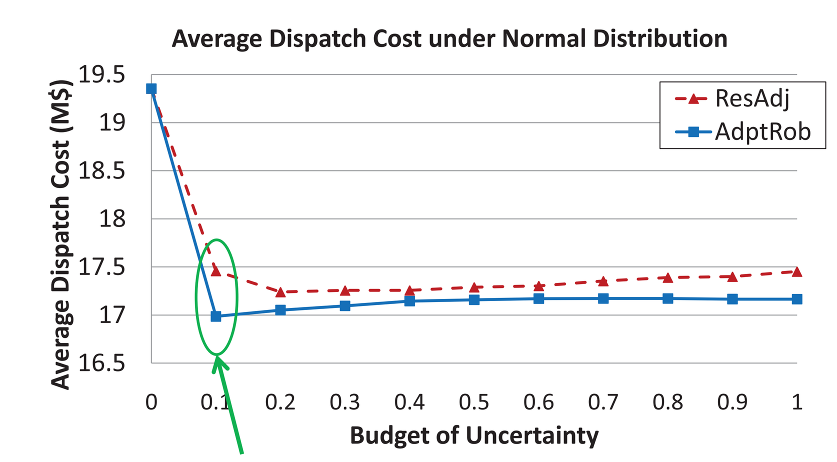
Computational Results (I): Average dispatch cost



Avg Dispatch Cost Relative Saving := (ResAdj – AdptRob)/ResAdj 0.65% - 2.7%

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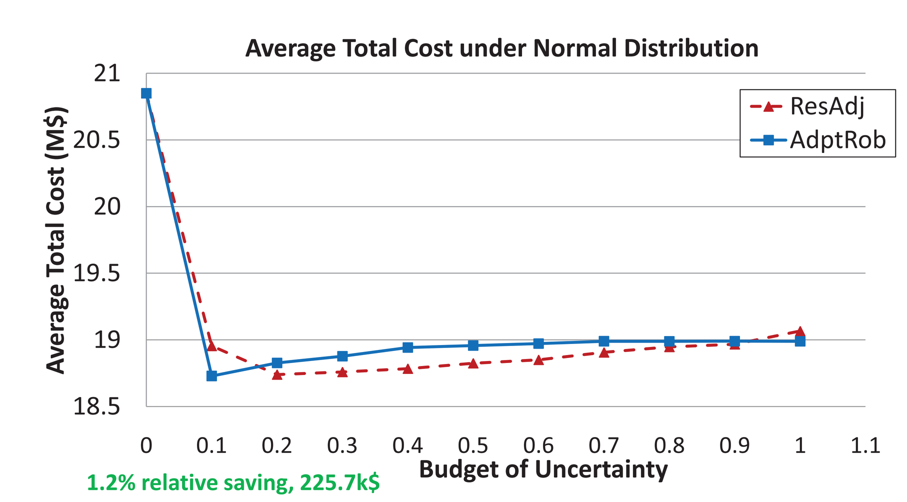
Computational Results (I): Average total cost



Avg Total Cost Relative Saving := (ResAdj – AdptRob)/ResAdj -0.84% - 1.2%

Fixed cost is around $1.8Million or 10% of total cost

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Computational Results (II): Volatility of Costs

Budget of Uncertainty	AdptRob Std disp cost ($k)	ResAdj Std disp cost ($k)	ResAdj/AdptRob
0.1	47.5	687.5	14.48
0.2	46.4	687.5	8.62
0.3	45.4	377.8	8.32
0.4	44.2	366.7	8.29
0.5	44.1	377.2	8.55
0.6	44.0	370.9	8.43
0.7	44.0	377.1	8.58
0.8	43.9	370.7	8.44
0.9	43.9	357.9	8.15
1.0	43.9	361.0	8.22

Coeff Var: 44k/17.2M=0.25%
370k/17.3M=2.1%

Significant reduction in cost volatility!

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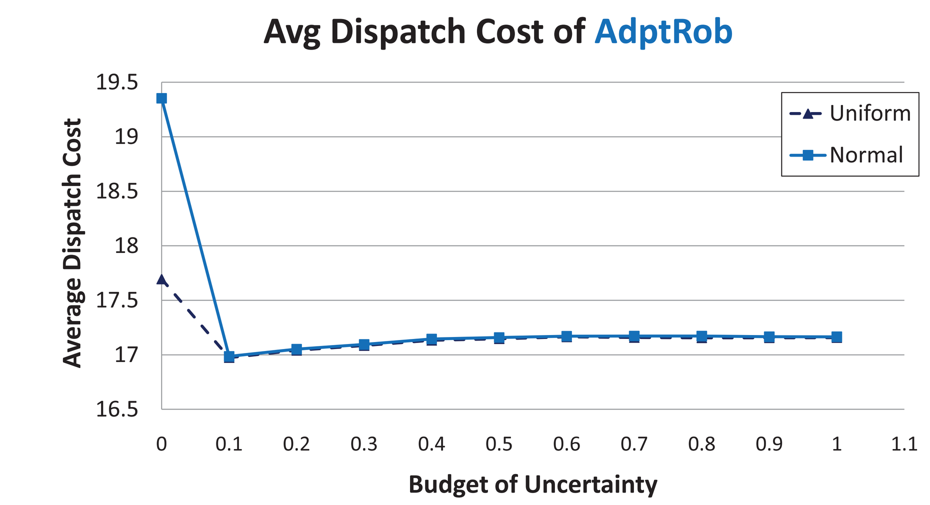
Computational Results (III): Robustness to Distribution



Relative difference: 0.0368% - 0.0920%
Absolute difference: $6.3k – $15.8k

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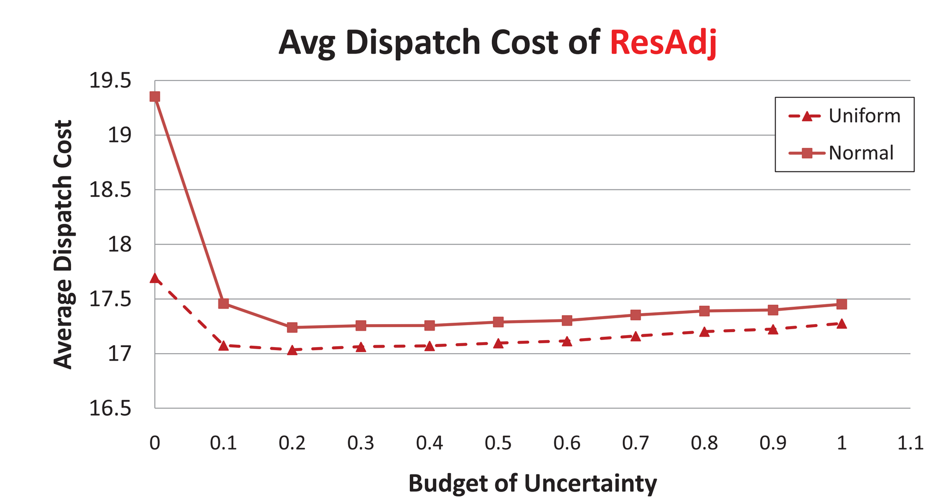
Computational Results (III): Robustness to Distribution



Relative difference: 1.00% - 2.19%
Absolute difference: $174.4k – $382.2k

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Conclusion and Business Implications

- saves dispatch cost (up to 2.7% $472.9k) → Economic Efficiency
- Significantly reduces cost volatility → Reduces Price & System Operation Volatility
- robust against load distributions → Data Driven Approach Demand Modeling

Reference: Adaptive Robust Optimization for Security Constrained Unit Commitment Problems, D. Bertsimas, E. Litvinov, A. Sun, J. Zhao, T. Zheng, submitted to *IEEE Transactions on Power Systems*

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Residential electricity disaggregation – Tailored consumption feedback in smart grids

M. Weiss, T. Staake, F. Mattern, E. Fleisch, and R. Larson

Increasing number of appliances drives residential energy conumpition

Managing energy use in existing buildings is crucial for overall improvements in energy intensity. About 40% of the total energy used in the US is consumed by the building sector[1].

Heating and cooling are the major end uses of energy in buildings. However, appliances increasingly contribute to the growth in energy consumption in residential buildings.

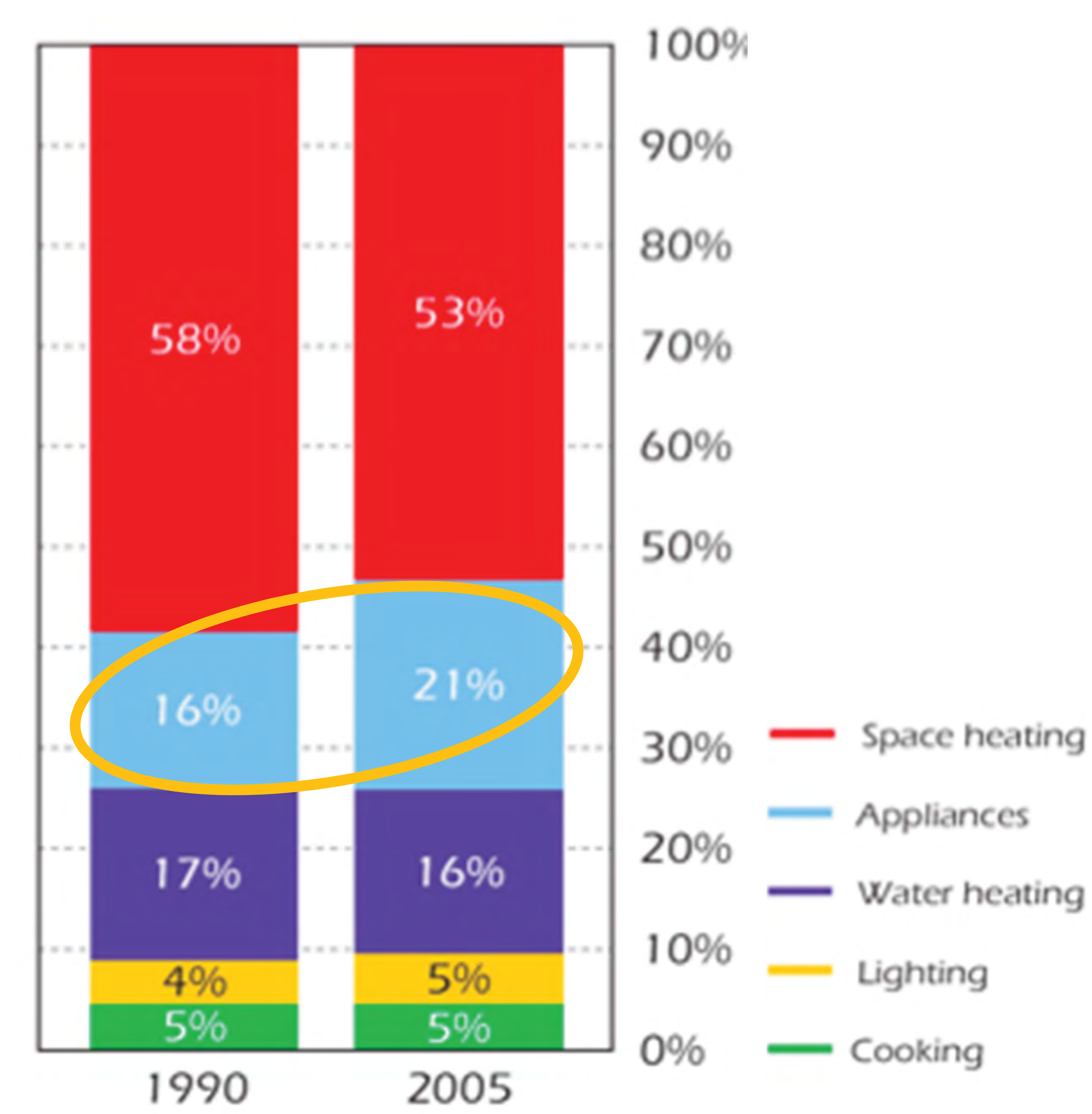
Data analytics of metering data allows us to auto-identify the consumption of an individual appliance:

→ tailored energy feedback at no extra cost

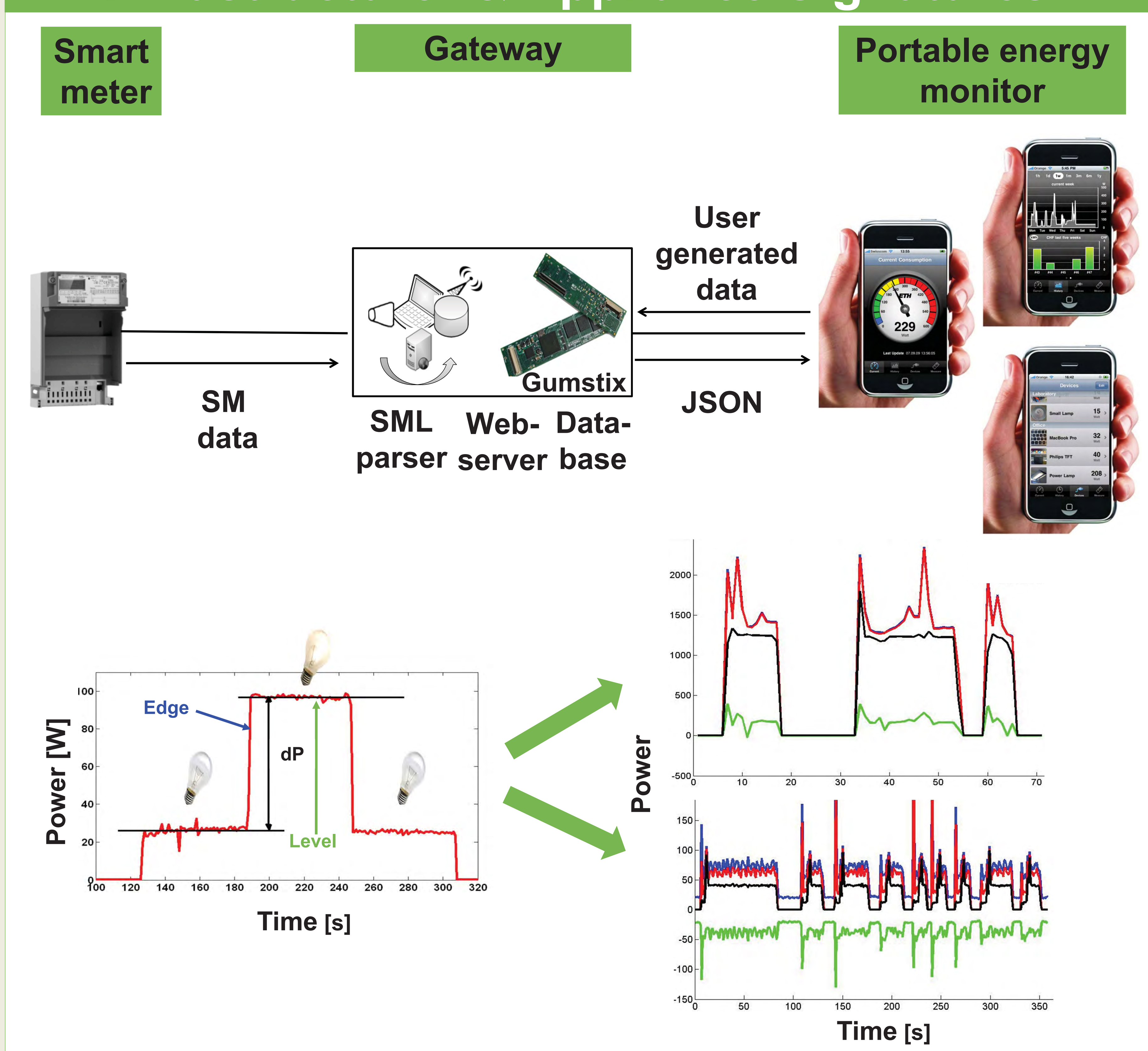
→ improved energy efficiency in combination with actuation

→ new business opportunities in the smart grid

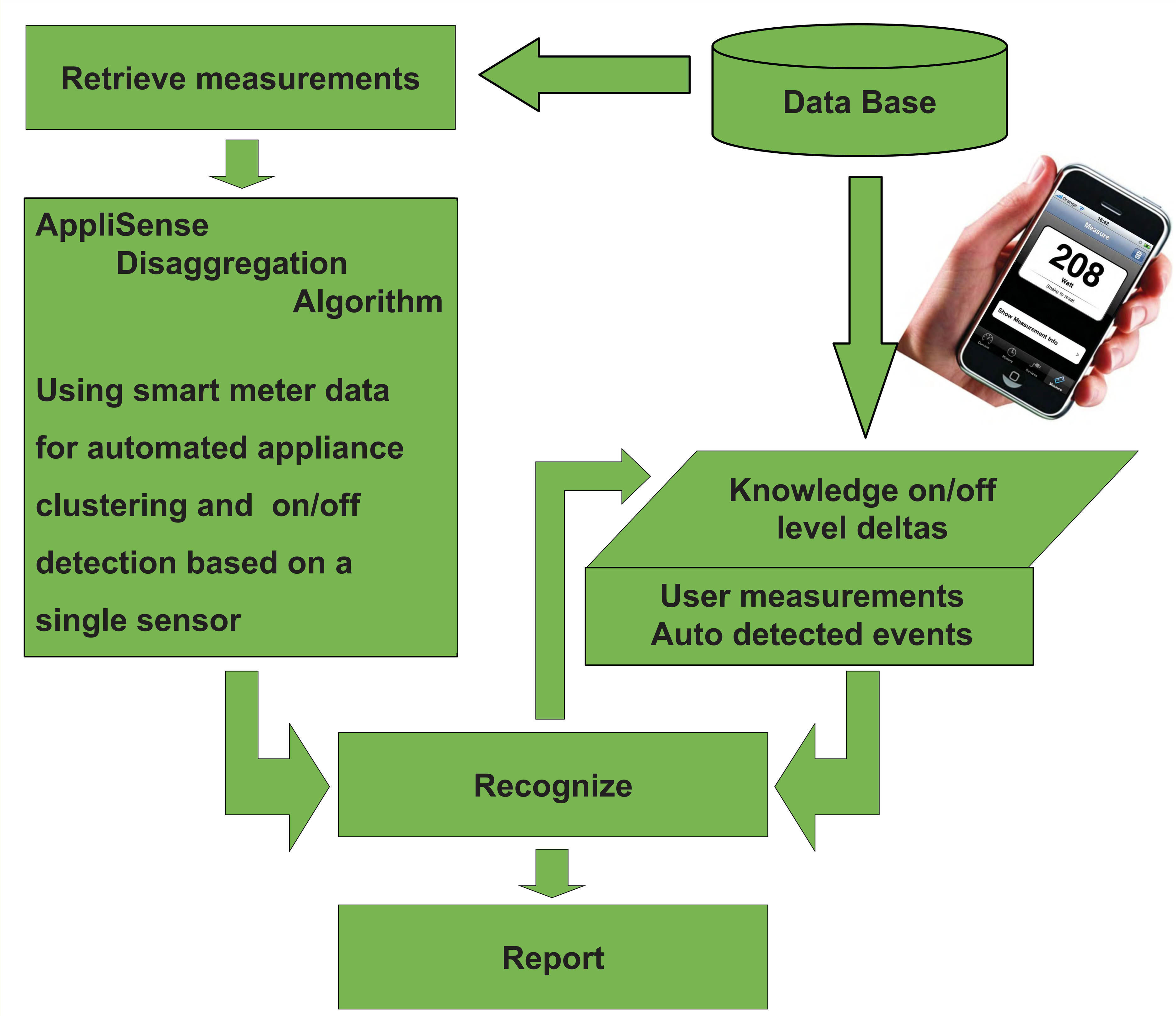
Household Energy Use by End-Use (IEA19)[2]



Infrastructure[3] & Appliance Signatures[4]



Leveraging Smart Meter Information



Results & Future Work

- Loosely coupled three component architecture.
- 91% recognition rate in lab study.
- Real-world deployment for over 6 months (9 million measurements for analysis).
- Algorithm refinements based on real-world data.
- Combine with smart power outlets.
- Input for automated heating control.
- Use data on a higher aggregation level (e.g., streets, regions, etc.).

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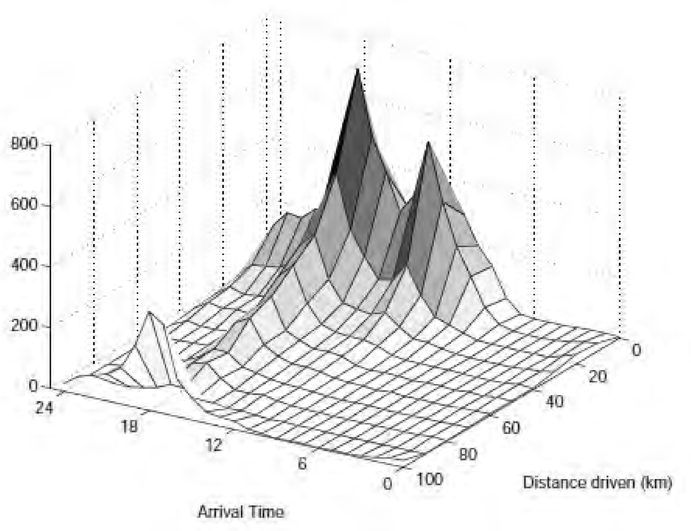
References:

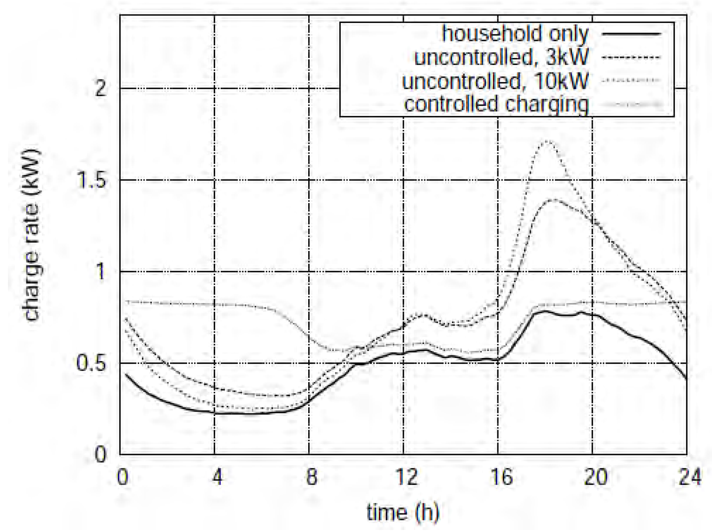
1. Annual Energy Review 2009, Energy Information Administration, 2010.
2. International Energy Agency (IEA) 2008. Worldwide Trends in Energy Use and Efficiency - Key Insights IEA 2008.
3. Weiss, M., Graml, T., Staake, T., Mattern, F., Fleisch, E., Handy feedback: Connecting smart meters with mobile phones. Proc. MUM 2009, Cambridge, UK, 2009.
4. Weiss, M., Staake, T., Mattern, F., Fleisch, E., PowerPedia - A smartphone application for community-based electricity consumption feedback. Proc. Smartphone 2010, Gwangju, South Korea, 2010.

Various Power System Impacts of the Large Scale Adoption of Electric Vehicles

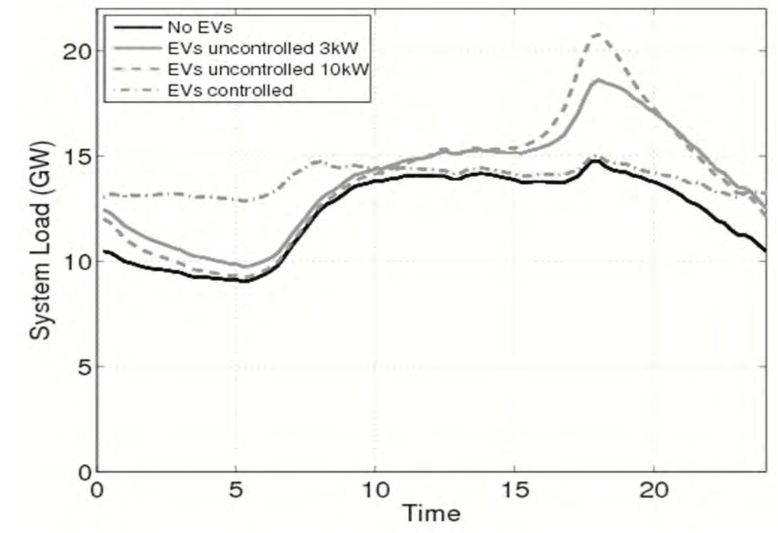
R.A.Verzijlbergh, Z.Lukszo, M.D.Ilić



Driving patterns: distribution of daily driving distance and home arrival time.



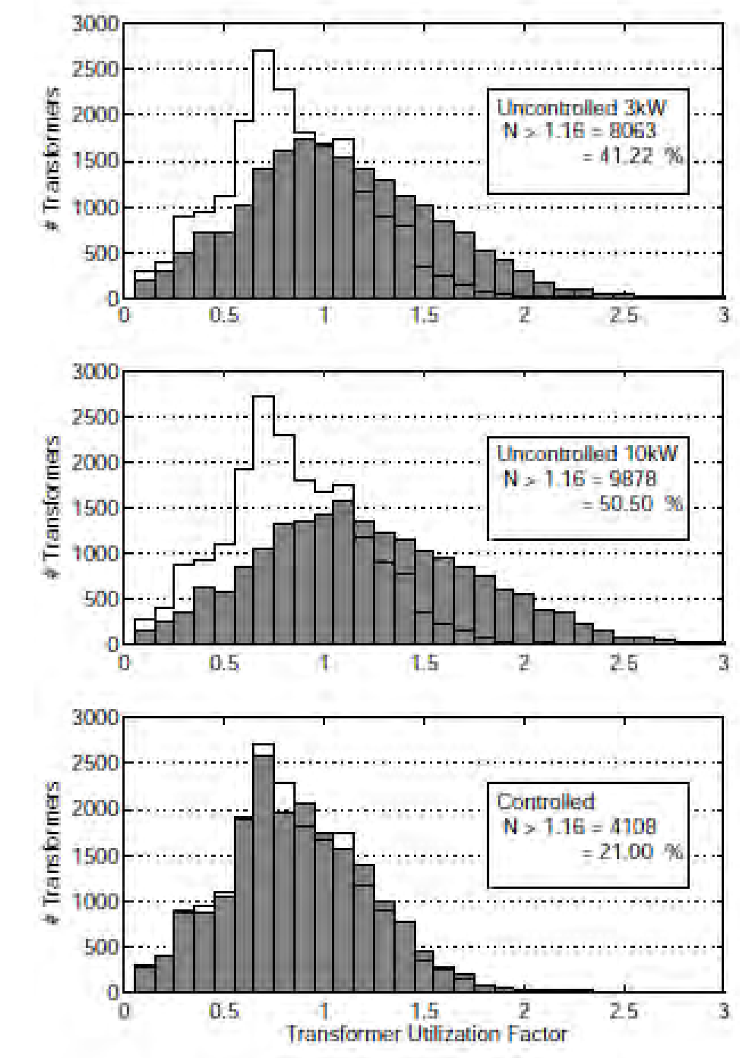
Aggregated household load for households with one EV.



Increased system load in the Netherlands for 75% of all passenger cars electric.

Charge Profiles

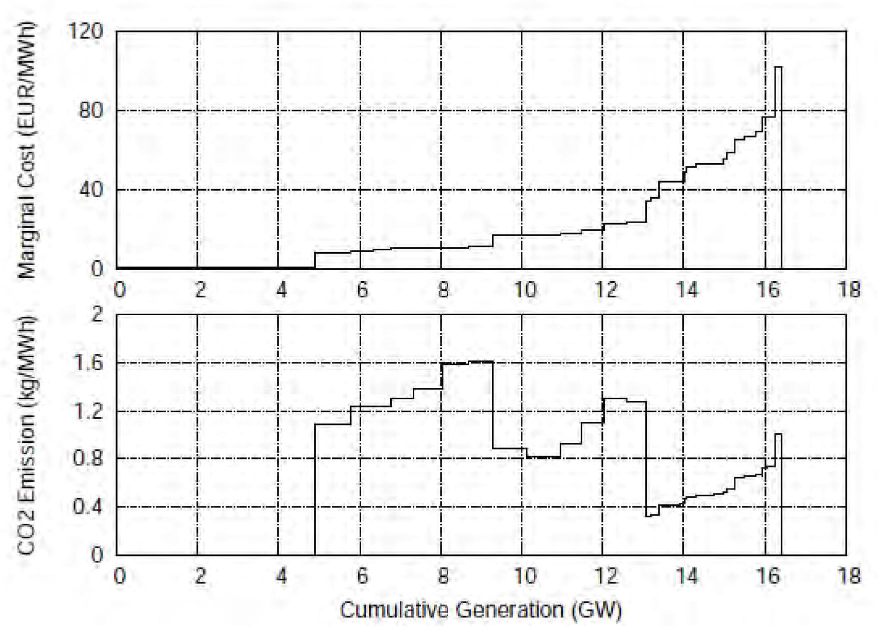
Aggregated profiles of electric vehicle charging are derived with the use of car driving patterns. From a dataset derived from interviews with roughly 18000 car drivers, we have used daily driving distances, home departure times and home arrival times to construct various charge scenarios.
In the uncontrolled charging scenario, a car driver comes home, plugs in the EV and starts charging with a constant power (either 3kW or 10kW) until the battery is full. The controlled charging scenarios takes into account at what time the car has to be full for the next home departure. It will charge the battery when the 'normal' household load is minimum, normally during the night.
The effect of applying charge control is immediately clear when adding the EV load to the household or system load. In the uncontrolled charging scenario the peak increases, but less pronounced than often suggested.



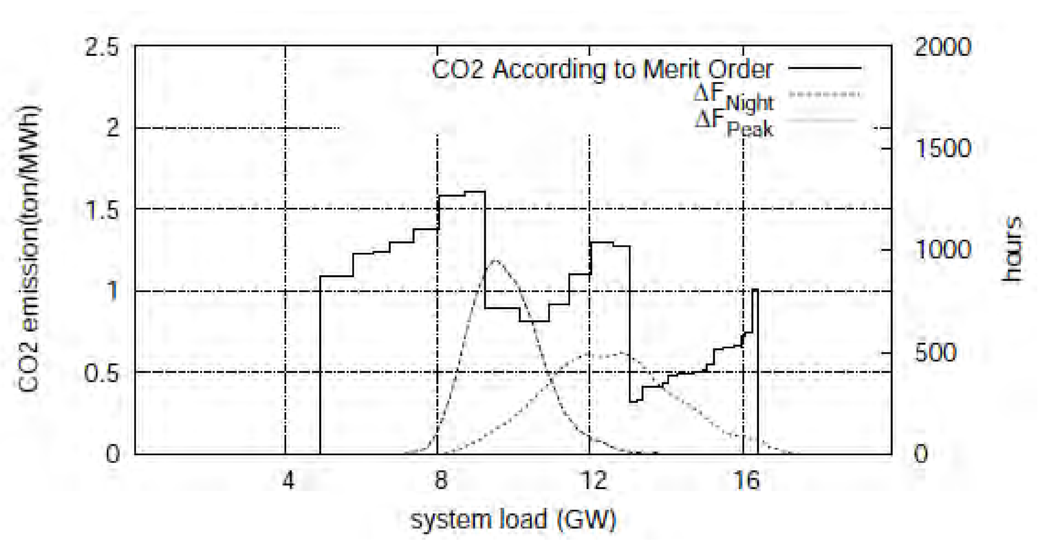
Histograms of MV/LV-transformer loading factors in three different EV charging scenarios and 30 years of 1% consumption growth. The background histogram denotes the situation with growth only (no EVs).

Grid assets

To study the impact of EV charging on distribution grid assets, a large number of distribution networks in the Netherlands have been analyzed. The EV load profile has been added to measured load profiles on LV cables, MV/LV transformers and MV-cables, which have been adjusted to account for 30 years of 1% electricity consumption growth. The resulting loading factors (1 denoting a grid asset loaded at nominal capacity) can hence be interpreted as the loading factor that would result from 30 years of electricity growth *plus* the extra load caused by EVs. An aggressive penetration scenario of EVs is assumed: 75% of all passenger cars after 30 years; these numbers are in line with government targets.
It was found that uncontrolled charging of EVs will lead to roughly 25% extra overloaded MV/LV-transformers compared to the situation without EVs, see figure on the left. For LV and MV cables, these numbers are much smaller: approximately 10% extra overloading due to EVs.
In the controlled charging scenario there will practically no extra overloaded grid assets. These results give an indication of the possible value of smart charging for distribution system operators.



Merit order and emissions ranked according to merit order of a portfolio based on the German technology mix (left to right: wind, nuclear,lignite, coal, gas)



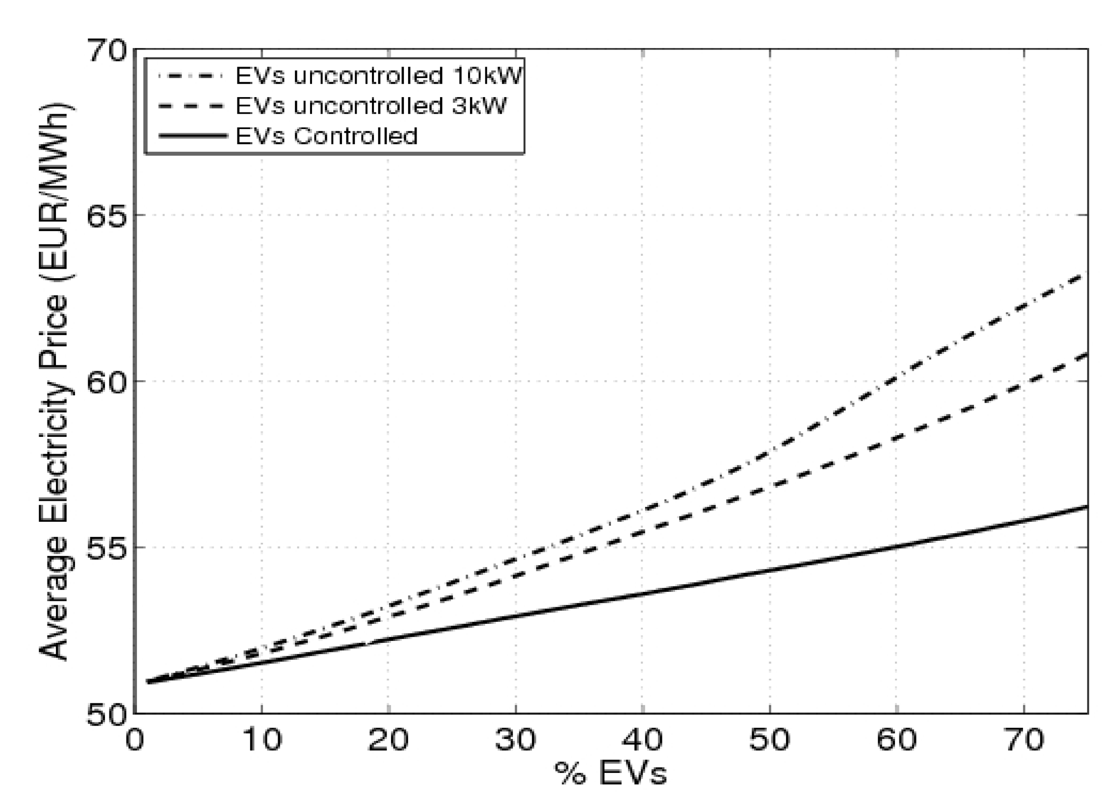
Emissions ranked according to merit order and extra load hours with a given system load due to EV charging. The emissions caused by EV charging are the overlap of the emission curve and the extra load hours.

Emissions of EV charging

The emissions caused by EV charging will generally depend on the units that are dispatched to meet the extra system load due to EV charging. This, in turn, strongly depends on various factors such as the total portfolio of the power system, the amount of intermittent generation, CO2 prices, the time of charging and the amount of EVs present.
Using a simple merit order dispatch model, we have shown that the emissions are very sensitive to most of these factors. The figures on the left illustrate this point. It was also demonstrated that using the *average* CO2 intensity to calculate the expected emissions by EV charging leads to inaccurate outcomes.
These results imply that it is very hard to control the emissions caused by EV charging in a liberalized market environment. For effective greenhouse gas reductions in the transport sector, additional policy will thus be required.

Electricity costs

The merit order dispatch model has also been used to estimate generation costs involved with EV charging. Generally, the costs of charging will be higher than average electricity costs when charging at the system peak, and lower when charging at night. It is interesting to see how average generation costs (based on the marginal costs of the marginal plant) are influenced by the amount of EVs in the system. The figure on the right shows that, as expected, costs are most influenced in the case of uncontrolled charging. This figure also shows that one has to be cautious when modeling EVs as price takers in electricity markets.



Increase in average electricity price as a function of the fraction of EVs (of a total of 8 million passenger cars) in the Netherlands. Instantaneous prices are calculated on the basis of marginal cost of the marginal plant according to the Dutch merit order; figure denotes yearly average.

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[3] R. Verzijlbergh, Z. Lukszo, J. Slootweg, and M. Ilic, "The impact of controlled EV charging on residential low voltage networks," accepted for the 8th IEEE International Conference on Networking, Sensing and Control, 2011.

TU Delft

Control of a Liquid Fluoride Thorium Reactor With Biogeography-Based Optimization

Rick Rarick, Mehmet Ergezer, Looja Tuladhar, Dr. Dan Simon, Dr. Charles Alexander and Dr. F. Eugenio Villaseca
Cleveland State University
Carnegie Mellon Conference On The Electricity Industry, March 8-9, 2011

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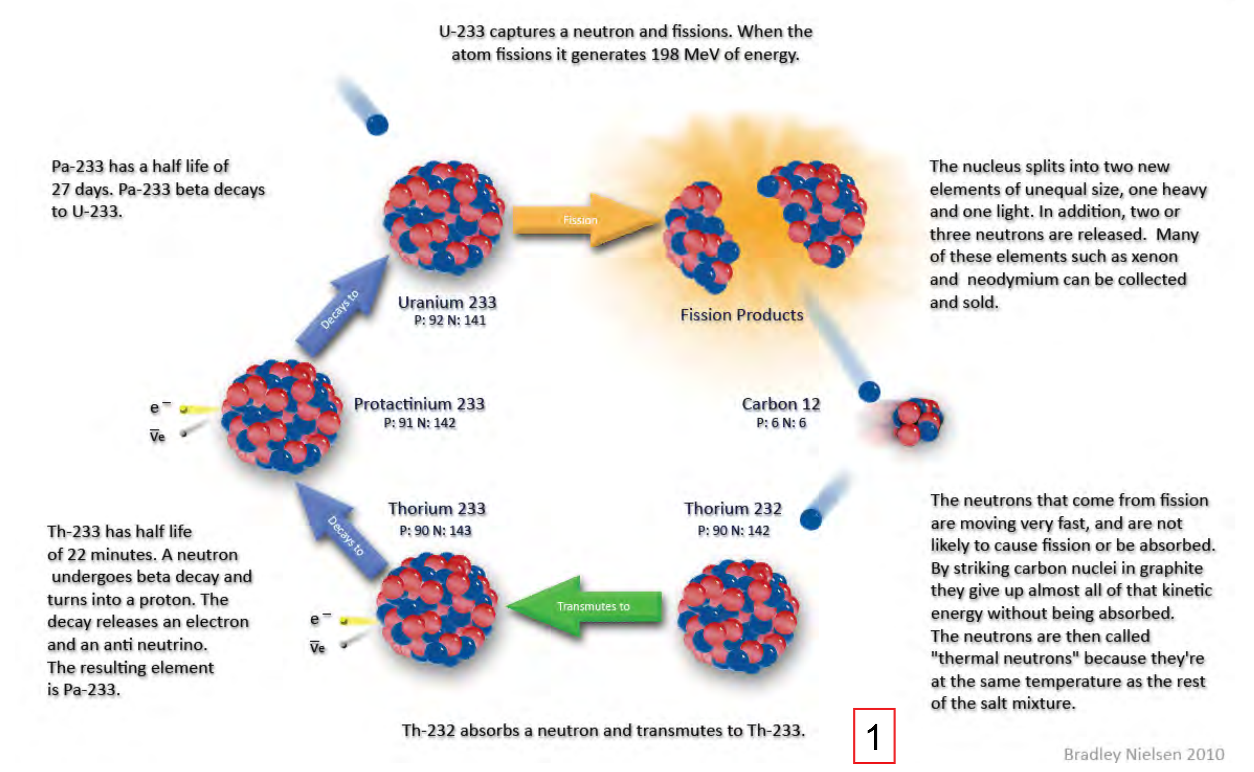
NSF Grant Number: 0826124
PI Names: Dan Simon, Jeffrey Abell

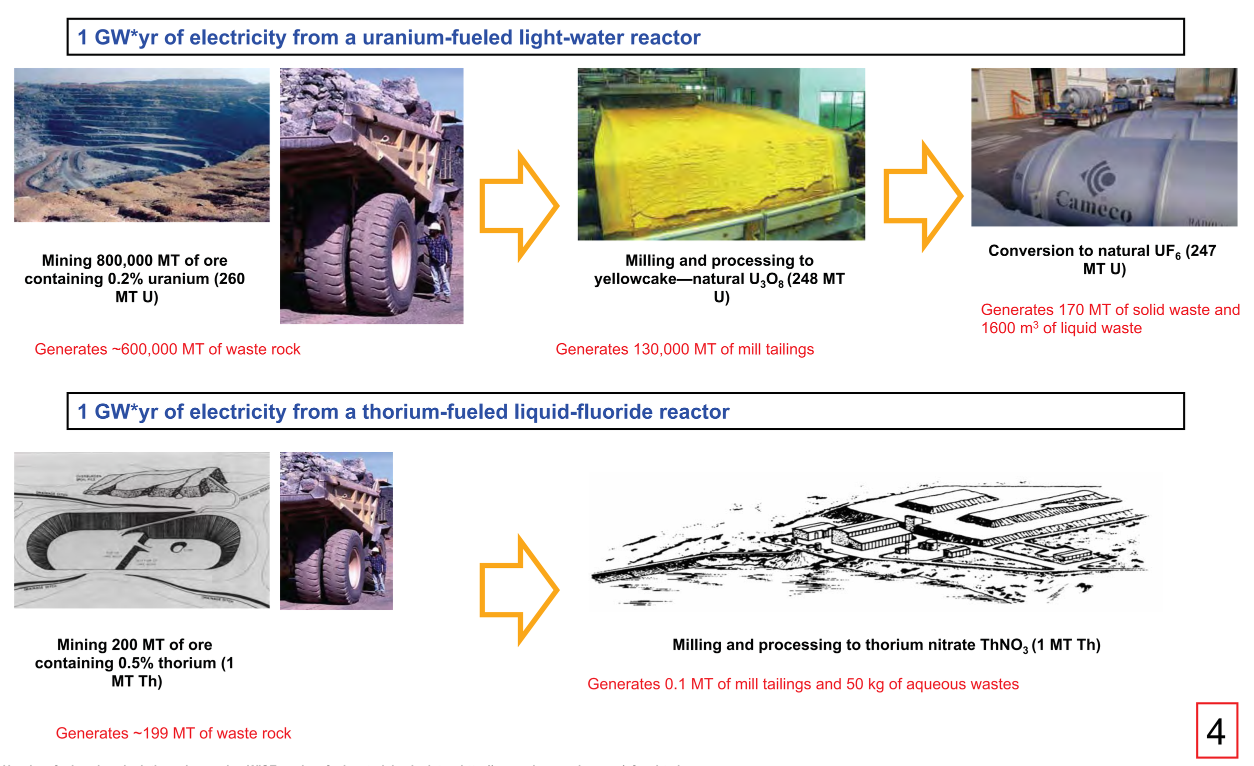
D.O.E Grant Number: DE-FC26-06NT42853
PI: Charles Alexander

Thorium nuclear fuel cycle



1

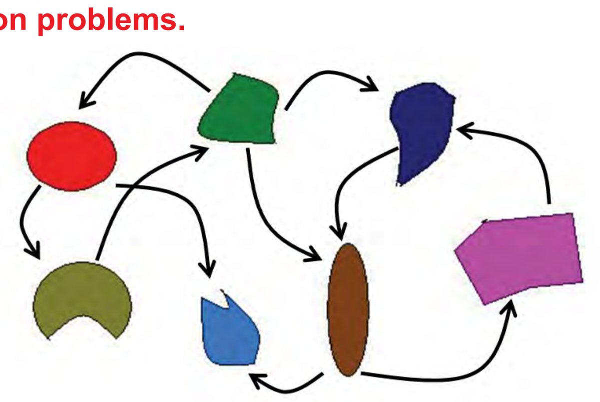
Waste generation for LWR and LFTR for comparable electrical output.



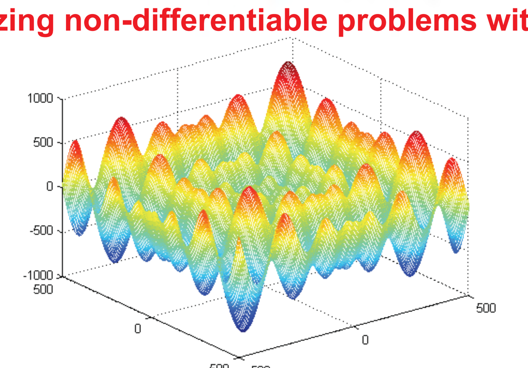
4

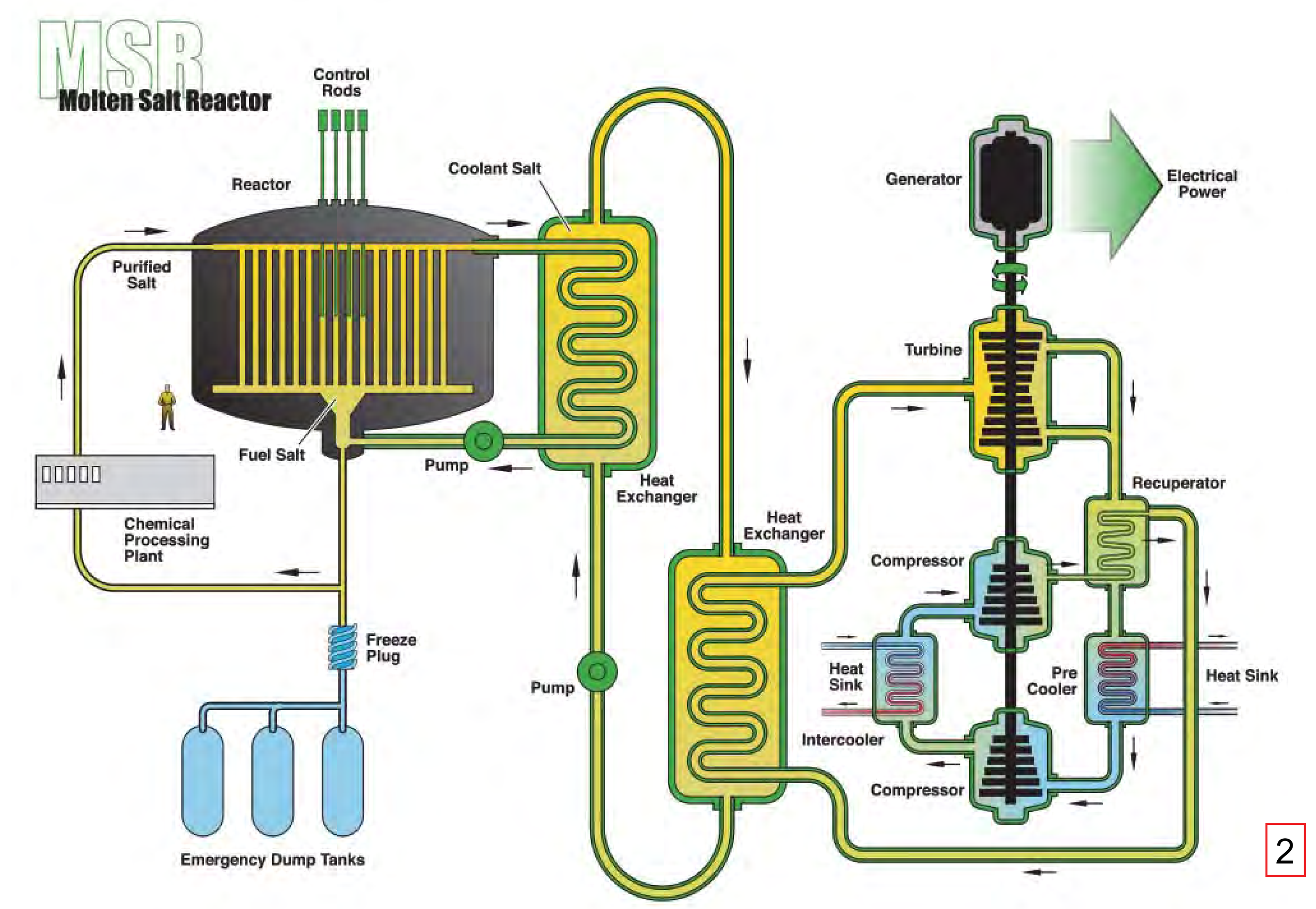
Uranium fuel cycle calculations done using WISE nuclear fuel material calculator: http://www.wise-uranium.org/nfcm.html

BBO models the migration of species in search of better habitats to solve global optimization problems.



BBO excels in optimizing non-differentiable problems with high-number of variables.





2

Thorium has a high energy density.

6 kg of thorium metal has the equivalent energy of

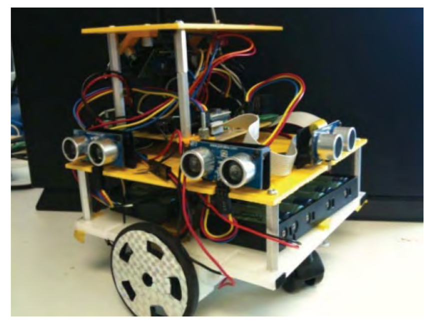
=

600 train cars of brown coal

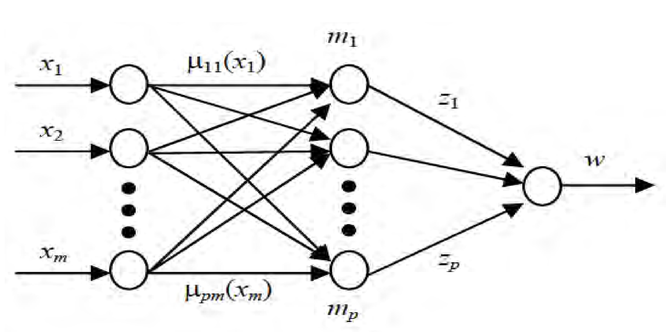
300 kg of enriched (3%) uranium

4

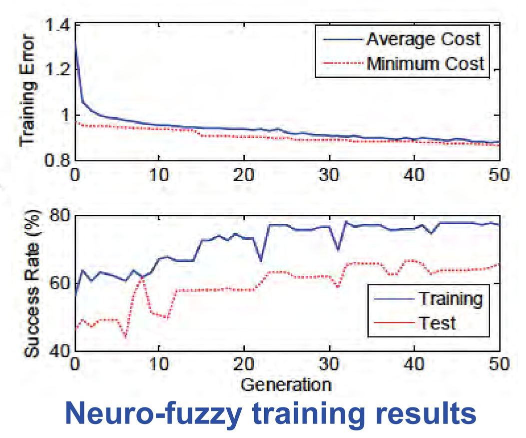
BBO has been applied to control robot swarms and detect cardiomyopathy.



Intelligent robotics control 5



Neuro-fuzzy classification network



Neuro-fuzzy training results

6

Thorium is far more common and cheaper than uranium.

1. Lemhi Pass on the Montana-Idaho border has enough thorium to power the US for millennia.
2. 500 tons of thorium can supply all US electricity needs for one year.

3

A Liquid Fluoride Thorium Reactor (LFTR) power plant is

1. Safe: Reactor is inherently stable and cannot melt down.
2. Clean: Generates much less waste than a Light Water Reactor (LWR), thorium is totally consumed.
3. Proliferation Resistant: Very difficult to make weapons, easily detectable.
4. Efficient: Runs at higher temperatures than coal and LWRs, so attains higher efficiency.
5. Lower Capital Cost: Much smaller than comparable LWRs and do not require a containment dome.

Why should we choose Thorium instead of Uranium for nuclear power?

1. Thorium is about four times more abundant than uranium. LFTRs are cheaper, simpler, more stable and sustainable than uranium LWRs.
2. Uranium reactors yield weapon-grade plutonium and, hence, are better for bomb production. This was a factor in choosing U over Th as a nuclear fuel during the early nuclear development in the post-war arms race.
3. For 1GW of electricity production in a year, Th produces less than one percent of the waste of U.
4. Current waste reprocessing systems for U are complicated and expensive. They convert solid material to liquid and then back to solid, whereas LFTR reprocessing is much simpler.

3

Control Design

1. Develop mathematical model of reactor, turbine, and generator
2. Controlled states
   a. Reactivity
   b. Heat flow
   c. Fluid flow
3. Control techniques:
   a. PI controllers
   b. Artificial neural networks
4. Optimize control design with BBO
   a. MIMO, nonlinear system
   b. Constrained optimization
   c. Multi-objective optimization

A Review of the Focus Areas for the Integration of Distributed Energy Resources (DER) to the Grid

Markets

Service Provider

Commercial Services

Energy Services

'Smart' Metering

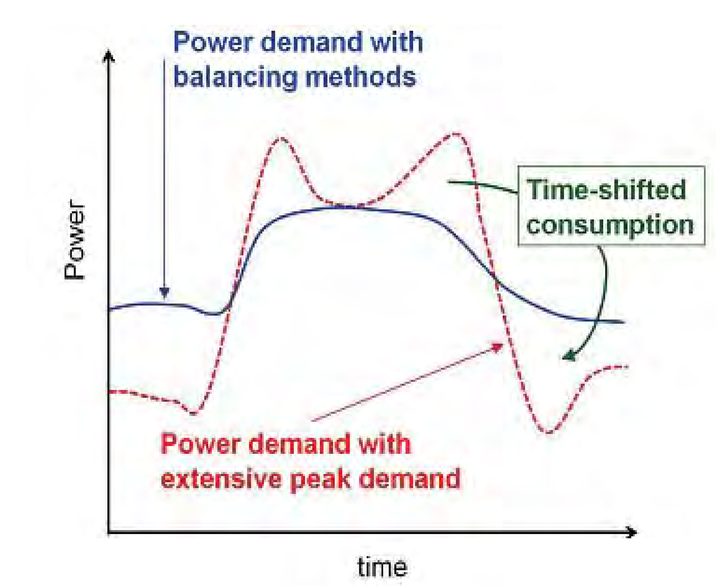
Customer Domain EMS

Demand Response

Problems Addressed

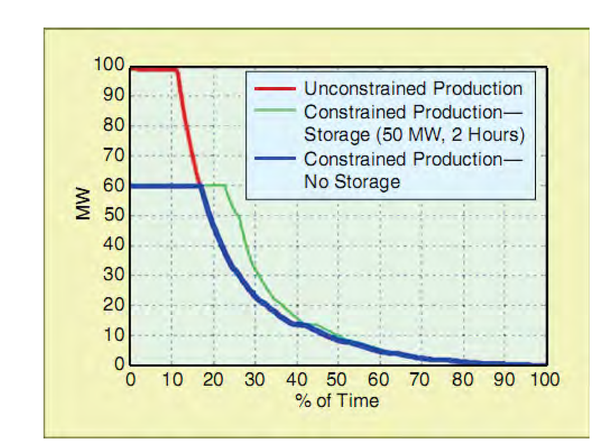
- Peak Shifting
- Expensive Regulation
- Slow Response Time
- High losses – Transmission Efficiency

Dispatchable Loads



Distributed Generation

Storage



Automation and Software Services

Problems Addressed

- Multiple Protocols
- Need for Real time Pricing
- Dynamic changes in Network Topology
- Latency issues in communication

Storage

Problems Addressed

- Intermittency of Renewables
- Peak Demand Regulation
- Optimal Transmission Capacity

Carnegie Mellon

Akhilesh Magal

Equity and efficiency in residential electricity pricing

Shira Horowitz[1*] and Lester Lave [1,2]

1. Introduction

Wholesale and retail electricity prices are decoupled for most residential customers. Wholesale prices change in real time to reflect the marginal cost of power. They can range from negative values on a cold night when there is an excess of power to the price cap of $1000/MWh on a hot summer afternoon. Residential retail customers, however, typically pay a flat rate that reflects a load weighted average of power prices.

Flat rates lead to electricity pricing that is both inefficient and inequitable. It is inefficient from an economic perspective since marginal price is not equal to marginal cost and consumers may be over- or under- consuming power at any point in time. It is inequitable since customers with low peak demand are essentially subsidizing customers with high coincident peak demand.

In this work we calculate which residential customers are subsidizing other customers. We break it down by customer class, income level and consumption levels.

2. Data Set

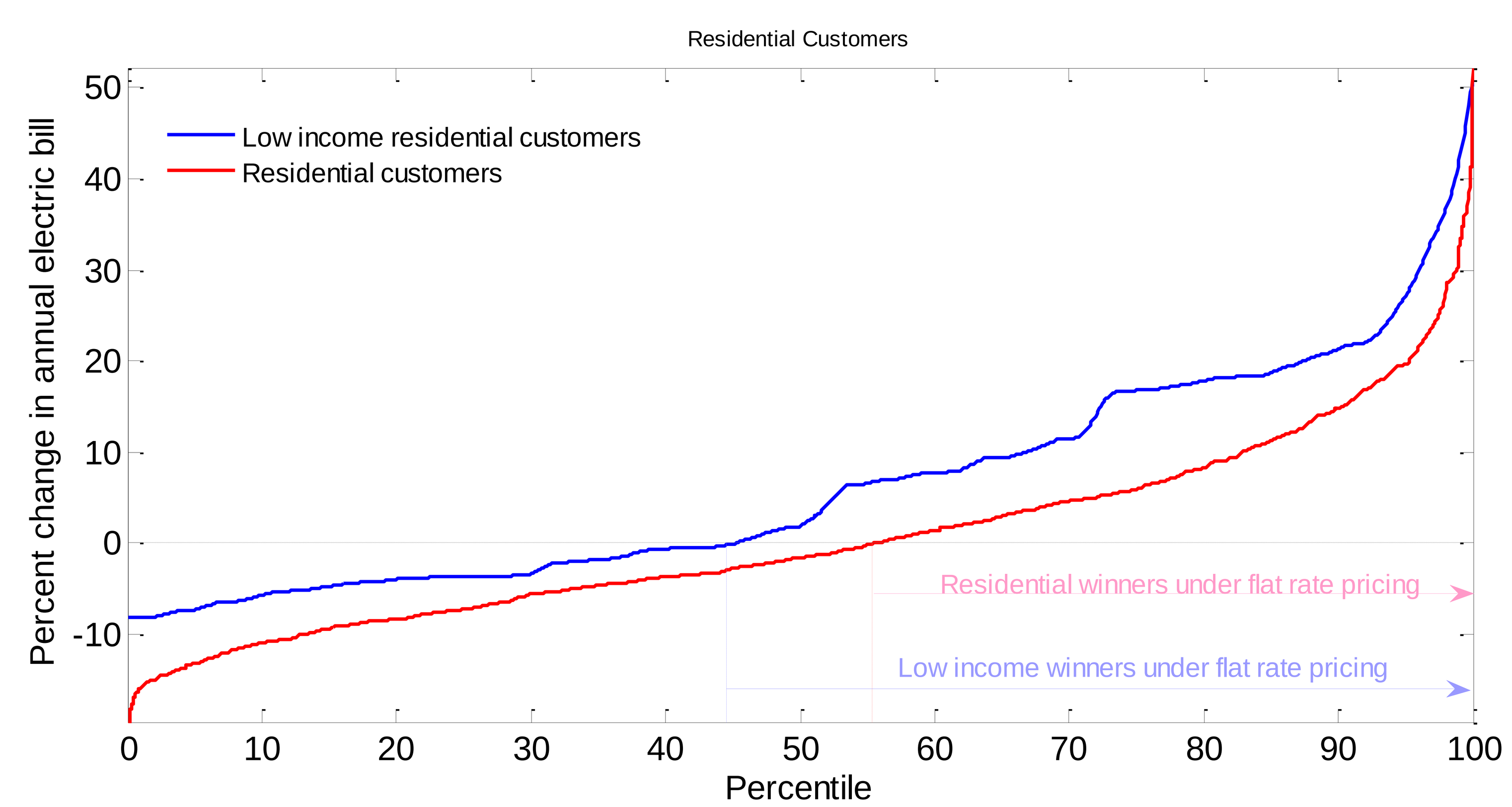
Our data set consists of hourly electricity usage from 1260 Commonwealth Edison (ComEd) residential customers in the greater Chicago area during 2007 and 2008. All of the customers were paying flat rates for power. They fall into 4 customers classes: (1) single family homes (65% of residential customers), (2) multi-family homes (i.e. apartment buildings – 30%), (3) single family homes with electric space-heating (1%) and (4) multi-family homes with electric space-heating (5%).

We use data on whether customers received any subsidies as a proxy for income. We divide customers into only two classes – high and low income.

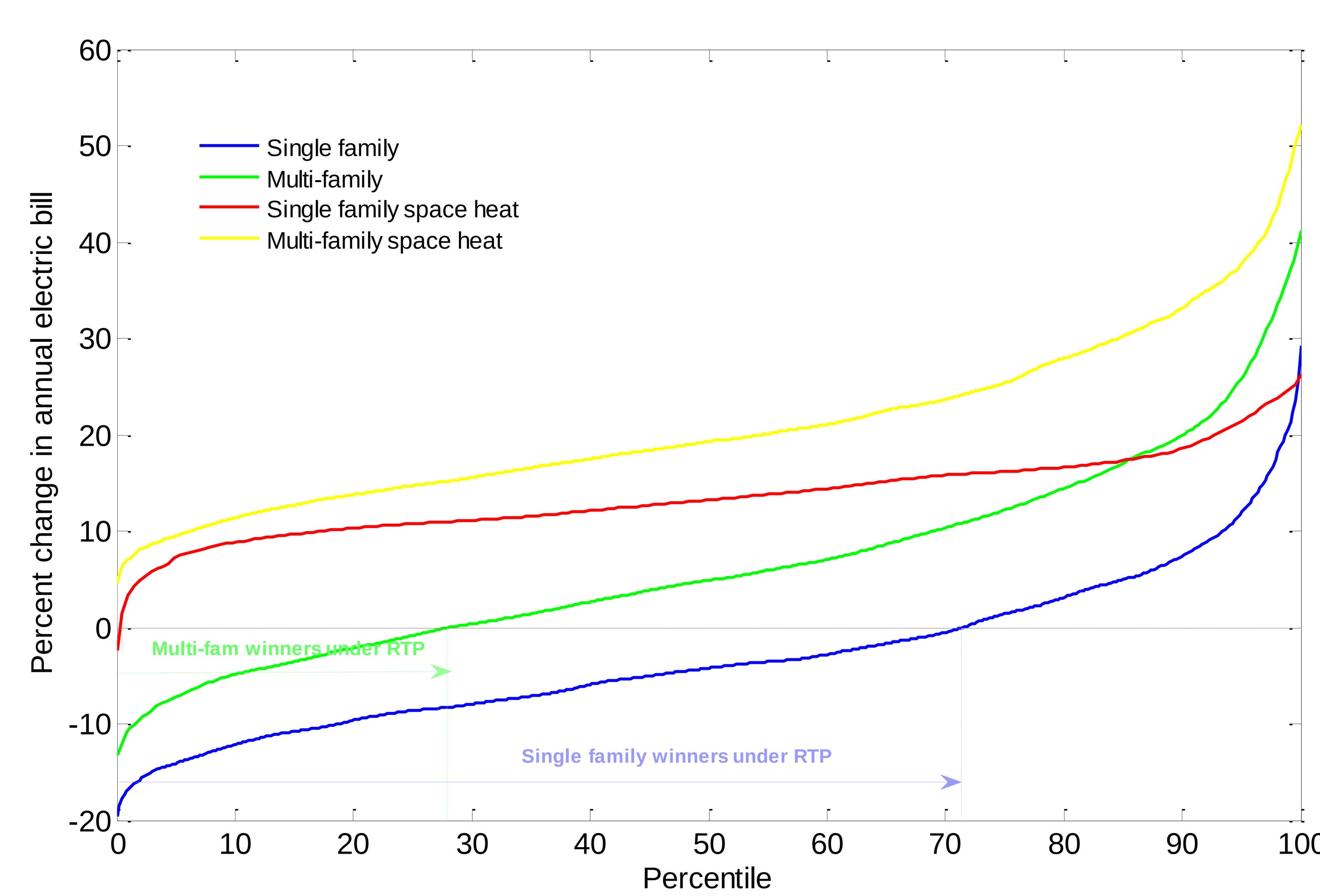
3. Analysis

We calculate what flat rate customers would have paid for electricity had they been on the ComEd residential real time pricing rate and compare this to what they paid under a flat rate.

Had all residential customers been on real time pricing (RTP)in 2007 and 2008 without any behavior change, net annual bill savings would have been **$120 million**. 55% of al residential customers end up savings money under RTP. This however means that 45% of customers lose money. Low income customers fare better under the status quo. Only 45% of low income customers save money under RTP, while 55% actually lose money.



Some customer classes do much better under RTP, while others benefit under flat rates. Single family customers – the biggest group – do best under RTP, with more than 70% saving money. Fewer than 30% of multi-family customers save money under RTP. All electric space heating customers lose money under RTP, however they consist of less than 6% of



ComEd's residential customers.

Non-space-heating customers with higher consumption and higher peak demand tended to save more under RTP. Electric space-heating customers who consumed more tended to lose more .

5. Policy Implications

There is significant net savings if residential customers paid marginal instead of average prices because of a risk premium hat customers pay for the certainty of a flat rate. Even if ustomers are not willing or able to change their behavior, here are overall savings if a switch is made to RTP. If ustomers can respond to high electricity prices by lowering heir demand, than savings for customers will be greater and nclude more people.

There are groups however, that end up losing money ınder RTP. Low income customers, electric space heating ustomers and multi-family customers lose money overall ınder RTP. These groups have the least ability to respond to luctuating prices . If a switch is made to RTP, it is important to provide these customers with additional subsidies or technology to respond to changing price.

While there is room for significant savings and economic efficiency improvements under RTP, there are significant equity issues to consider. Under flat rate pricing, 55% of residential customers are essentially subsidizing the use of the remaining 45% of customers, however, larger customers are subsidizing smaller customers and higher income customers are subsidizing lower income customers. If a switch to RTP is made, it is important to ensure that these customers do not end up losing out in the process.

Acknowledgments

This work was supported by the National Science Foundation and The Department of Energy. Commonwealth Edison provided the data used in the analysis. The authors would like to thank Fallaw Sowell (CMU) for his comments and Anne Pramaggiore, Val Jensen, Scott Caron and Jon Hargreaves from ComEd for their help with acquiring and understanding the data.

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Add Value of Distributed Generation to Electric Energy Systems

Masoud H. Nazari and Marija Ilić

Motivation

- T&D losses in U.S. are more than **6.5%**. It means **270** Billion KWh per year is dissipating in Transmission and Distribution lines.
- **Distributed Generators (DG)** have this potential to reduce T&D losses.
- This paper identifies optimal approaches in order to enhance efficiency of distribution systems with large penetration of DGs.
- It also indicates approaches to evaluate dollar value of loss minimization.

Need for Analysis

Analysis needed to

- Determine impacts of DGs on power delivery losses.
- Develop optimization algorithms for optimal placement and utilization of DG units in order to minimize power delivery losses and maximize efficiency.
- Develop quantitative approaches in order to monetize loss reduction.

AC Optimum Power Flow Algorithm

- Objective of the optimization algorithm is to minimize power delivery losses
- Two degrees of freedom
  - Optimizing the location of DGs
  - Optimizing the voltage set of DGs
- Limitations are power flow constrains and physical limits of lines and generators

Given $\{P_L\} = \{P_{L_1}, \cdots, P_{L_n}\}$

$$\{P_G^*\} = \min_{P_G} \sum_{i=1}^{N_G} \left(\tilde{P}_{G_i}\right)$$

subject to loadflow equations:

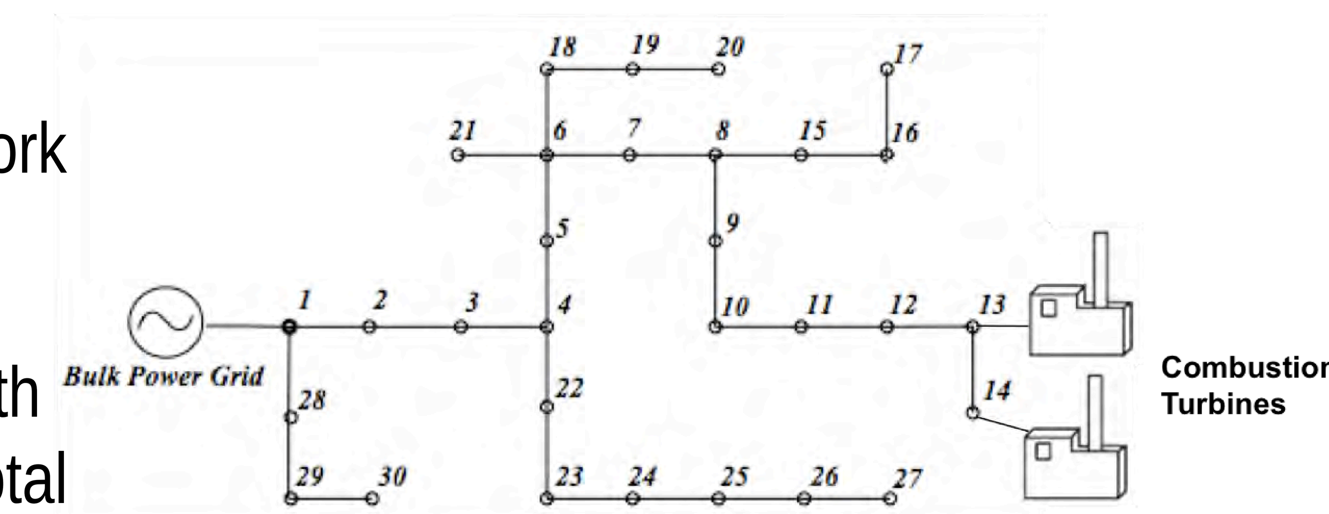
$$P_{ij} = G_{ij}\left(V_i^2 - V_iV_j\cos\delta_{ij}\right) + B_{ij}V_iV_j\sin\delta_{ij}$$
$$Q_{ij} = B_{ij}\left(V_i^2 - V_iV_j\cos\delta_{ij}\right) - G_{ij}V_iV_j\sin\delta_{ij}$$
$$P_i = \sum P_{ij}$$
$$Q_i = \sum Q_{ij} + V_i^2 B_i$$

and other security operation constraints such as:

$$|P_{ij}| \le P_{ij}^{\max}$$
$$P_i^{\min} \le P_i \le P_i^{\max}$$
$$V_i^{\min} \le V_i \le V_i^{\max}$$
$$Q_i^{\min} \le Q_i \le Q_i^{\max} \quad i \in \text{all buses}, i \ne j$$

Optimal placement and utilization of DGs (case study)

- Using **AC OPF** for optimum placement and utilization
- Using **IEEE 30-bus** distribution network test system



- Two **Combustion-Turbines** (C-T) with capacity of 750 kW providing **10%** of total demand (15 MW) could reduce **50%** (700 kW) of delivery losses
- This implies that **1MW** of **DG** could cancel out **1.47MW** of **central generation**.

Dollar Value of Loss Minimization

$$C_{DG} = \Delta P_{Loss} \times T \times LMP$$

- C_{DG} is added value of DG due to loss minimization in time interval of T
- ΔP_{loss} is average loss reduction due to DG in time interval of T
- T is time interval
- LMP is the locational marginal price of electricity in time interval of T (note if LMP changes by time, the average value of LMP is used)

Conclusions

- In general, loss reduction depends on the location and method of utilization of DGs (power factor and voltage sets) .
- Optimization methods such as AC OPF, are essential for planning and operation of modern distribution energy systems.
- Optimizing DGs in order to minimize power delivery losses could have large added value. This paper is a step to introduce systematic approaches to quantify the dollar value of loss minimization.

Acknowledgment

The authors greatly appreciate the financial support under the Portugal-Carnegie Mellon joint program.

Can a Wind Farm with Storage Compete in the Day-Ahead Market?

Brandon Mauch[1,2], Pedro M.S. Carvalho[2], Jay Apt[1]

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Introduction

Wind farms generally do not participate in day-ahead electricity markets because of the difficulty in scheduling dispatch from wind turbines a day in advance. We investigated the economic feasibility of a wind farm to participate in the day-ahead market if energy storage is collocated with the wind farm. Coupling a wind farm with a storage facility reduces the risk of relying on uncertain wind forecasts to dispatch electricity and allows some control over the dispatch. We used wind and price data to model a wind farm operating jointly with a compressed air energy storage (CAES) facility.

Wind and CAES Model

We modeled a wind farm with a CAES facility operating in the day-ahead market. Our model assumes the wind farm is a price taker, transmission is not constrained and all electricity offered to the market is accepted. The wind farm uses a forecast to determine the next day's dispatch schedule that will maximize revenue from hourly energy sales. Wind forecasts are received each day at noon and used to calculate dispatch quantities for the following day. While the wind generation for the following day is uncertain, we assume the price is known.

Input Data

Hourly wind forecast and generation data spanning the years 2008 and 2009 from a wind farm in the central region of the U.S. was used in the model. Values from 2008 were used to characterize the uncertainty of the wind forecasts. Data from 2009 was used for the model under the assumption that the forecast accuracy was not significantly different.

Market price data was taken from the Electricity Reliability Council of Texas (ERCOT) and the Midwest Independent System Operator (MISO). In the case of ERCOT, no day-ahead electricity market existed until very recently so real-time prices were used.

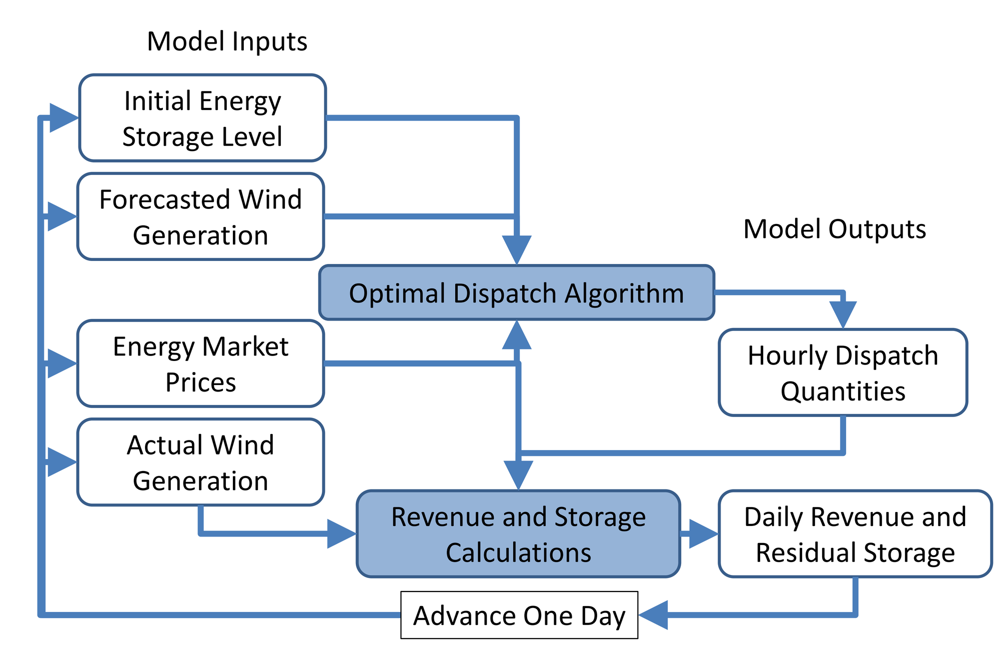
Acknowledgements:
This work was funded in part by the following:
- Alfred P. Sloan Foundation
- Electric Power Research Institute
- US National Science Foundation
- Portuguese Foundation for Science and Technology (*Fundação para a Ciência e a Tecnologia*)

Model Parameters

Wind Farm Capacity Factor	0.28
Wind Generation per Installed MW of Capacity	2445 MWh
CAES Expander Power to Wind Farm Capacity Ratio	0.9
CAES Expander to Compressor Power Ratio	1
CAES Storage Capacity at Full Power	15 hrs
CAES Heat Rate	3500 – 4500 Btu/MWh
Variable Cost of Storage	\$2.5 – \$3.5/MWh
Natural Gas Cost	\$4 - \$7/ 1000 cu ft

Model Algorithm

Optimal hourly dispatch values were computed each day from the wind power forecast values and the market prices. These dispatch values were then used with actual wind generation data to determine the hourly revenue the wind farm would have received.



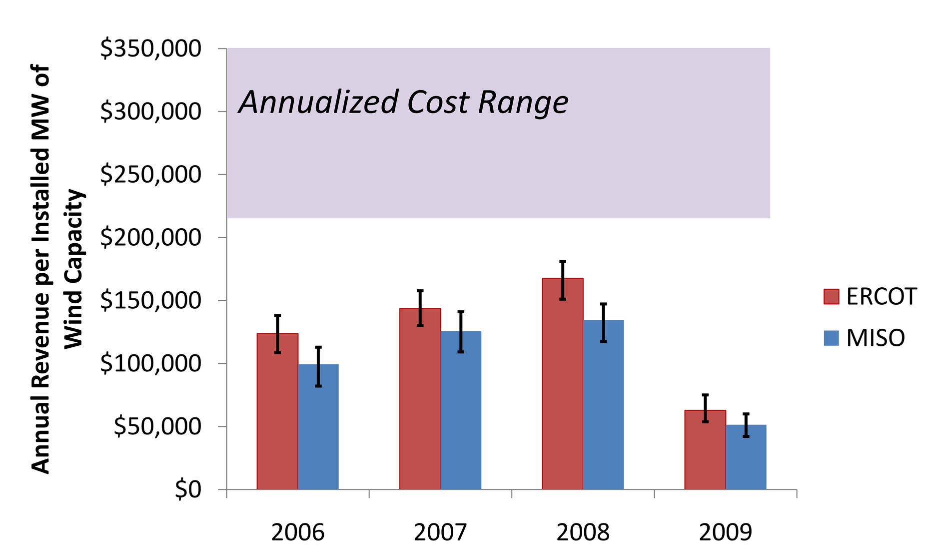
Wind and CAES Costs

Cost estimates for wind and CAES were taken from a literature review and the Energy Information Agency

	Capital Cost (\$/MW)	Fixed Annual Cost (\$/MW)
Wind	1.5 – 2.6 million	25 – 35 thousand
CAES	0.65 – 0.89 million	9 – 12 thousand

Model Results

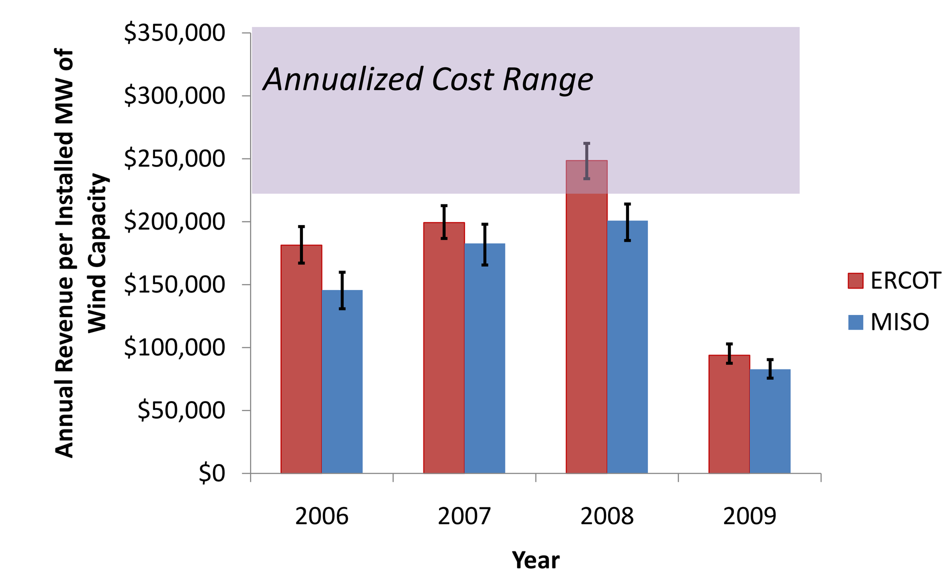
Annual revenue for the hypothetical wind farm was calculated using market price data from ERCOT and MISO for the years 2006 to 2009 . Annual revenue falls short of costs for all years.



Annual income was calculated using prices from ERCOT 2008 adjusted to estimate a carbon price. Results are still much lower than the estimated annual cost range of a wind-CAES system.

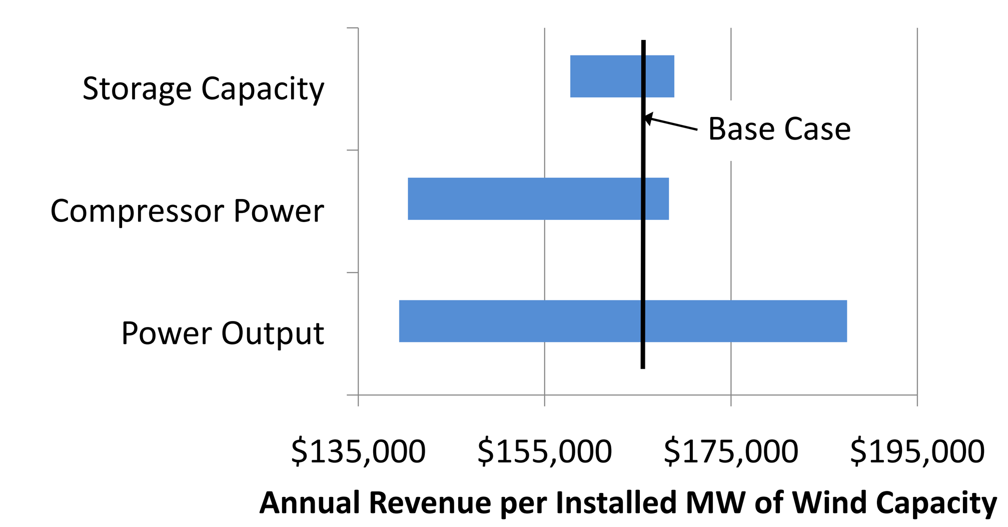
Carbon Scenario	Annual Revenue per Installed MW of Wind Capacity
\$0 per Tonne of CO_2	\$170,000
\$20 per Tonne of CO_2	\$190,000
\$50 per Tonne CO_2	\$220,000

Even with perfect wind forecasts, the annual revenue for all but one price scenario fell short of the estimated cost range.



Sensitivity Analysis

The sensitivity of each CAES parameter on annual income indicate that increasing the power output by 50% provides a modest increase in annual revenue while the other parameters have little affect.



Conclusion

Results from the model indicate that collocating energy storage with wind farms is not profitable at current market prices. The gap between annual costs and revenue for this approach can be thought of as the price of reducing carbon emissions. The implied cost per tonne of avoided CO_2 for a profitable wind – CAES system is roughly \$100, with large variability due to electric power prices. Unless energy prices increase substantially, other approaches may prove more cost effective.

Wind Speed Decomposition Modeling using Fourier Transform and Markov Process

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Motivation

- Short term, medium and long term wind speed trends require different data analysis that deals with changing frequencies of each pattern.
- Apply Fourier analysis to decompose wind speed signal into few components of different frequencies for different applications.
  1. Low Frequency range: for economic development such as long term policies adaptation and generation investment, time horizon- many years
  2. Mid. Frequency range: for seasonal weather variations and annual generation maintenance, time horizon: weeks but not beyond a year.
  3. High frequency range: for Intra-day and Intra-week variations for regular generation dispatches and generation forced outage, time horizon: hours but within a week

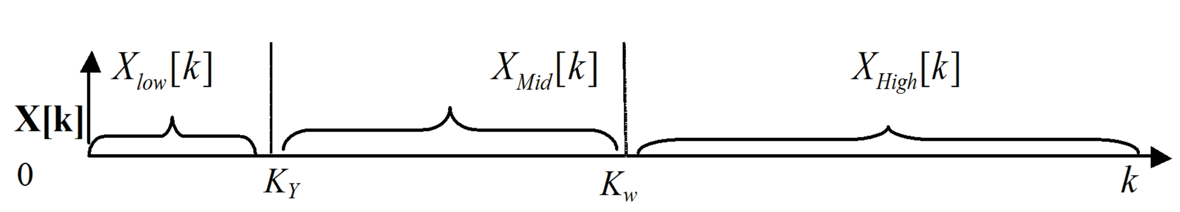
Signal Decomposition

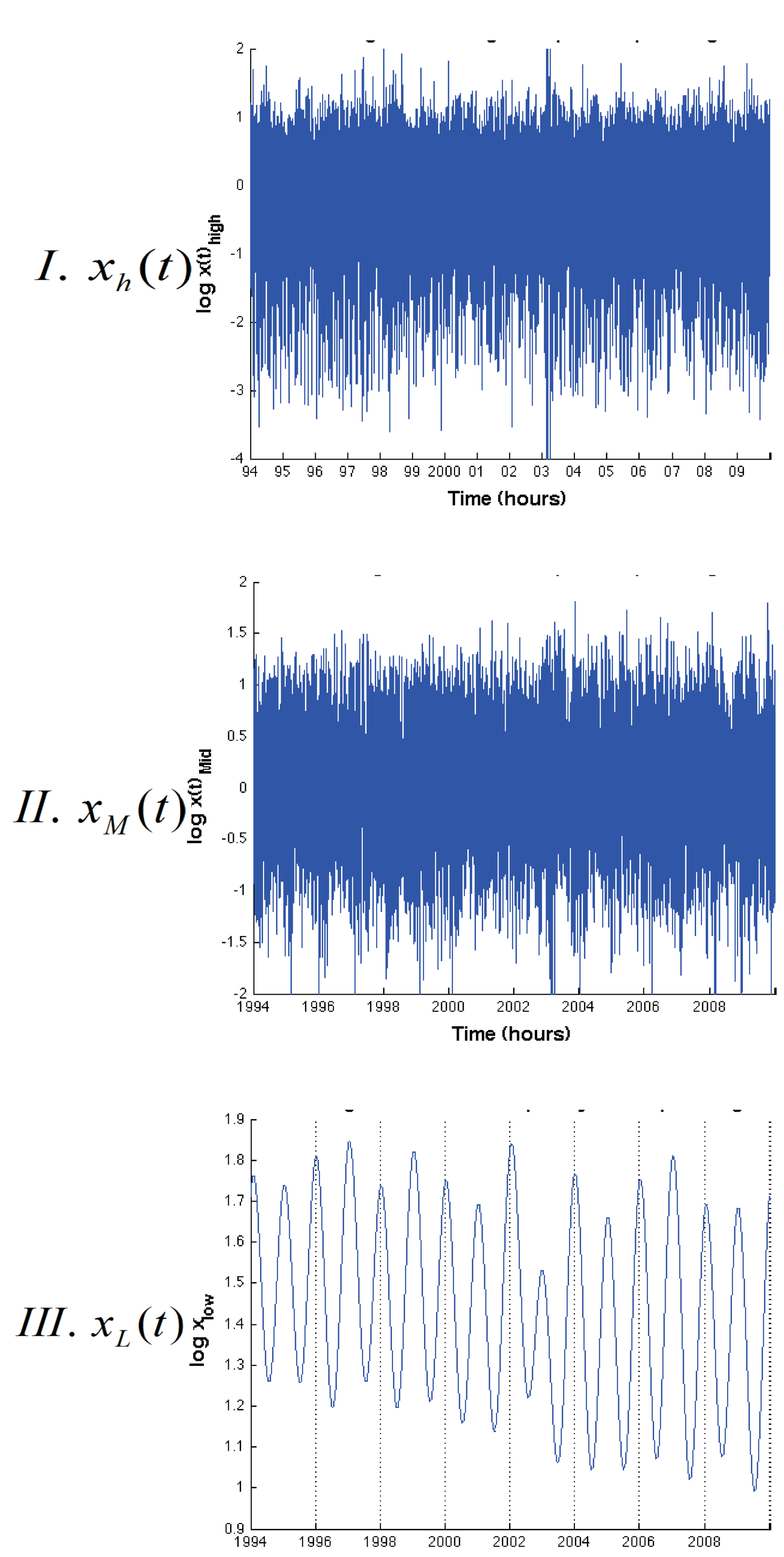
A Discrete Fourier Transform (DFT) of a natural logarithm of wind speed signal , X[k], decomposes the signal into low, medium and high frequency components, each of different K frequency index range as follows:

$$X_L[k]=\begin{cases} X[k]\,,\ 0\le k\le k_y \\ 0\ ,\ k_y\le k\le N-1 \end{cases}$$

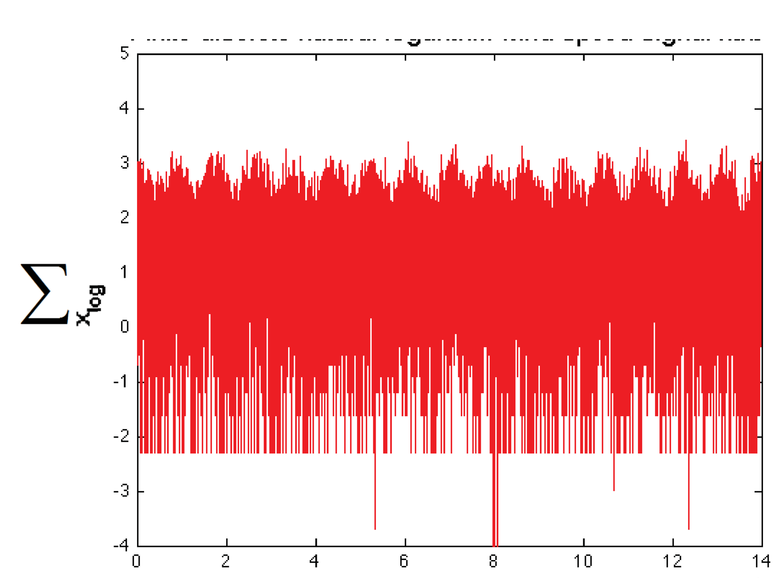
$$X_M[k]=\begin{cases} X[k]\,,\ k_y<k\le k_w \\ 0\ ,\quad otherwise \end{cases}$$

$$X_H[k]=\begin{cases} X[k]\,,\ k_w<k\le N-1 \\ 0\ ,\quad 0\le k\le k_w \end{cases}$$

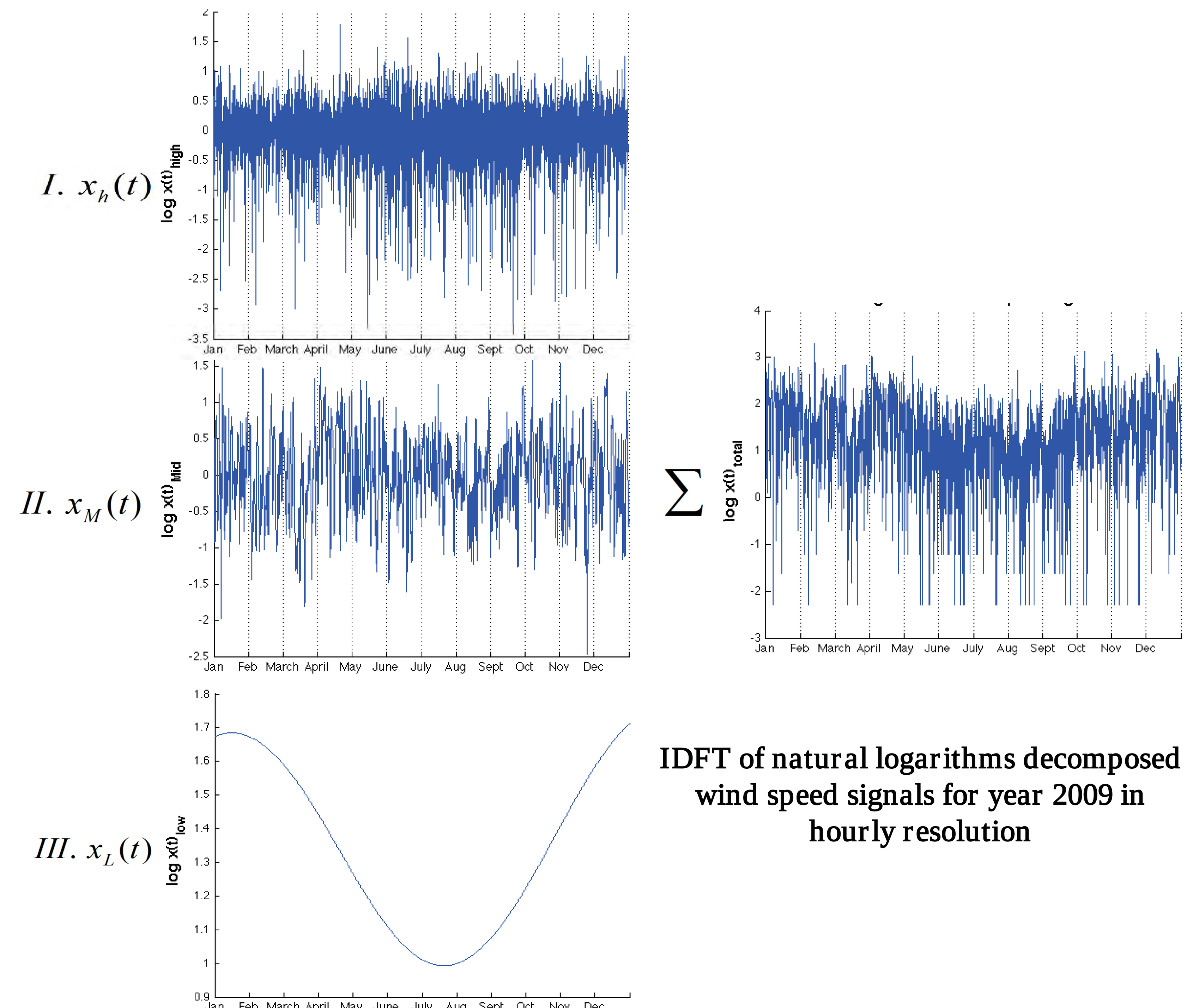




$$x_t(t)=x_h(t)+x_M(t)+x_L(t)$$



IDFT of natural logarithms decomposed wind speed signals for years 1994 - 2009 in hourly resolution



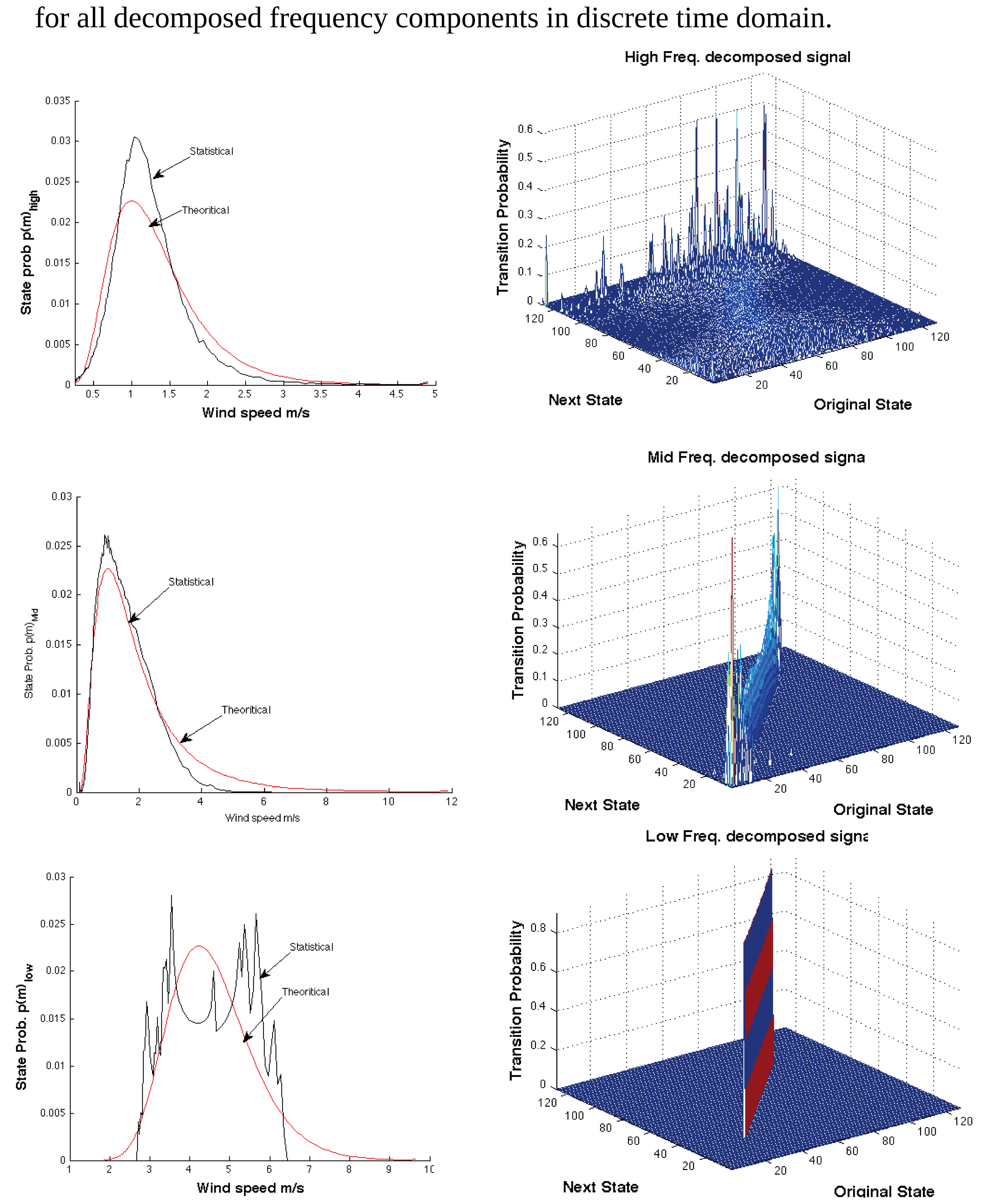
IDFT of natural logarithms decomposed wind speed signals for year 2009 in hourly resolution

Decomposed Discrete Markov Process of Wind Data

Markov process is defined as the likelihood of next wind speed value in state k conditioned on the most recent value of wind speed in state m.

$$P(X_k=i|X_m=x_m,x_{m-1},\ldots,X_1=j)=P(X_k=i|X_m=x_m)$$

Using a uniform quantization method and defining the initial and final states of the natural logarithms of wind speed signals, the distribution of the exponent of wind speed follows log normal with mean zero and standard deviation close to 1 for all decomposed frequency components in discrete time domain.



Carnegie Mellon

Adaptive Load Management (ALM)
Including Risk Management of Load Serving Entities¶

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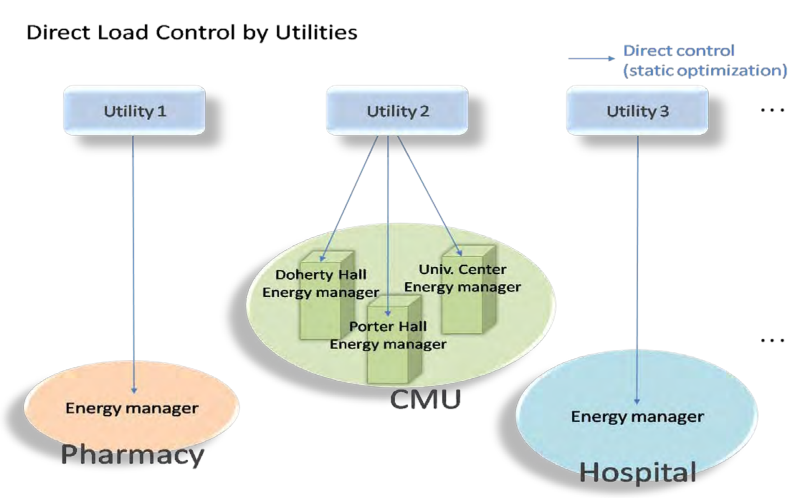
Background and Motivations for ALM

- **Load management so far**
  - Top-down control, one-way flow of information
  - Little information from end-users to the system level → due to complexity, unordinary commodity, etc.
  - Localized optimization on the end-users' level



- **How to include end-users information**
  - Load aggregators on behalf of end-users
  - Individual economic preference with respect to price signal : ***demand function***
    - From point-wise (price, quantity) information exchange → to functional information exchange

The Main Ideas of ALM

Incorporate *different end-users' economic preferences* into system optimization

- **Modeling end-users' different *economic preferences***
  - At a certain point, some prefer NOT to use electricity at a particular price while others do.
  - ***Demand function***
    : demand's willingness-to-pay with respect to consumption quantity
  - **Load aggregators**
    - Energy and information broker
      : Mediator between end-users and system/market both in ***financial and physical*** sense
    - Risk manager
- **Multi-layered optimization problem**
  - ***Primary layer***
    :End-user's utility maximization
  - ***Secondary layer***
    : Load aggregator's profit maximization
  - ***Tertiary layer***
    : System operator's social welfare maximization

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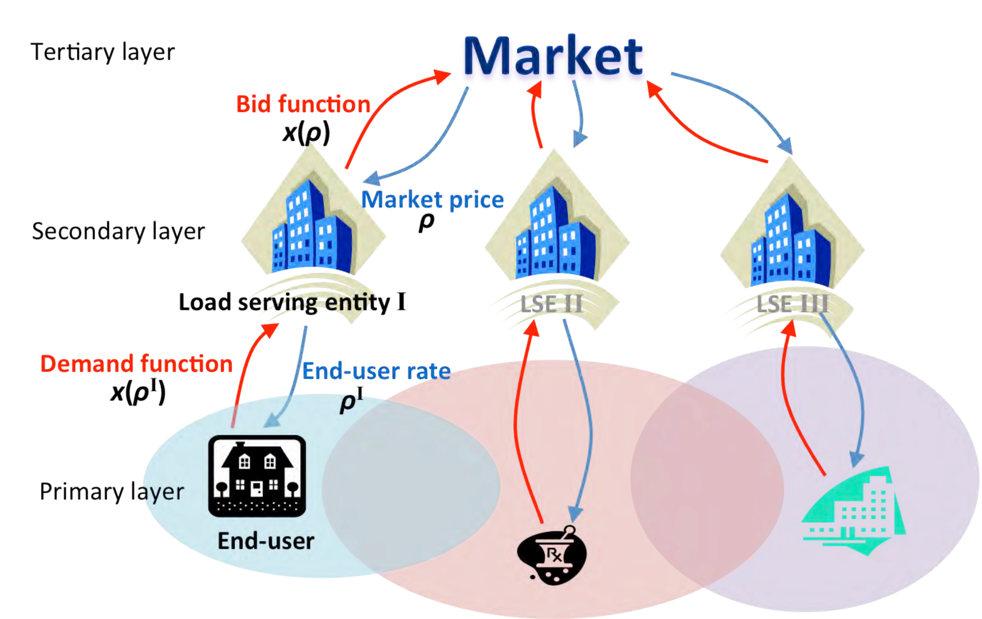
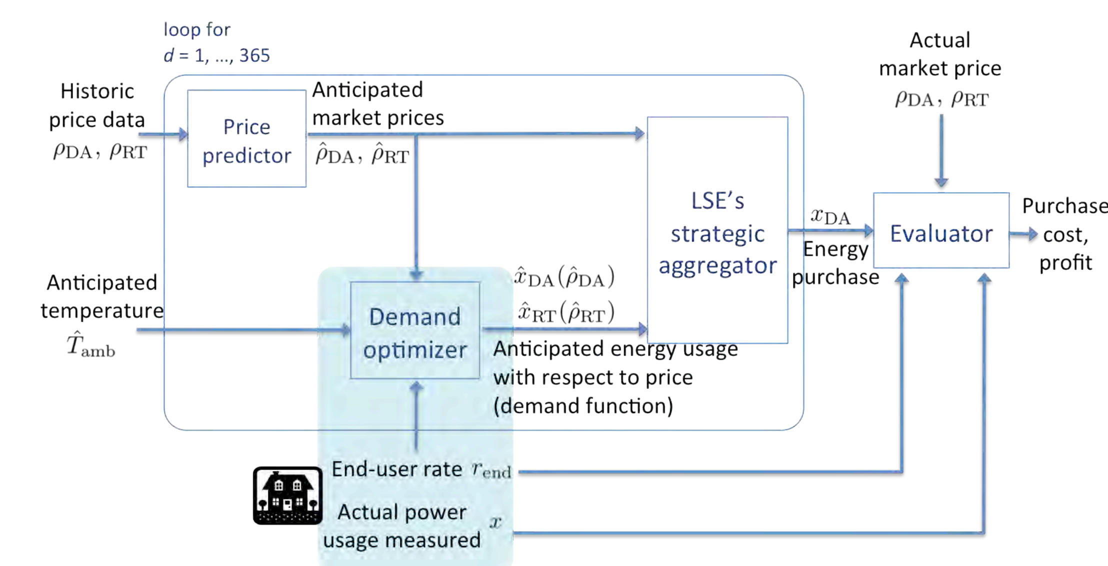
Information flow of ALM

- **View of the whole system**



- **Information exchange around LSE**



LSE's short-term risk management

- Day-ahead and real-time market optimization
  : **Markowitz optimization**
  - Minimizing the risk of return
  - With respect to the physical temperature constraints

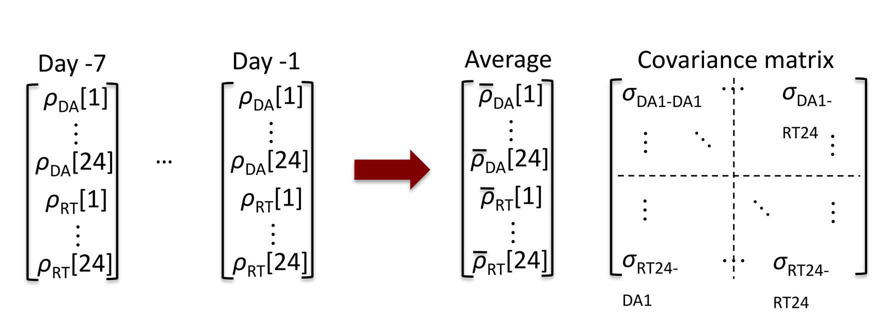
$$\min_{x} \; w_r x^T \Sigma_p x + w_c \bar{p}^T x + (T - T_{\text{set}})^T W_T (T - T_{\text{set}})$$

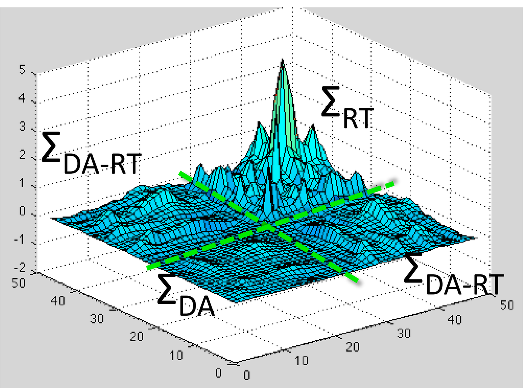
$$\text{subject to} \quad T[k+1] = \varepsilon T[k] + (1-\varepsilon)(T^{\text{out}}[k] + \gamma x[k])$$

$$x_{\min} \le x[k] \le x_{\max} \quad \forall k$$

$$\text{where } \Sigma_p = \begin{bmatrix} \Sigma_{\text{DA}} & \Sigma_{\text{DA-RT}} \\ \Sigma_{\text{DA-RT}} & \Sigma_{\text{RT}} \end{bmatrix}$$

- **Price processing** in price predictor
  - Covariance matrix
    - Shows correlation between two (different) random variables
      - 48 random variables
        → 48x48 matrix
    - Variance of real-time market price much higher
    - In our simulations
      - Input: Hourly day-ahead and real-time prices of the last 7 days



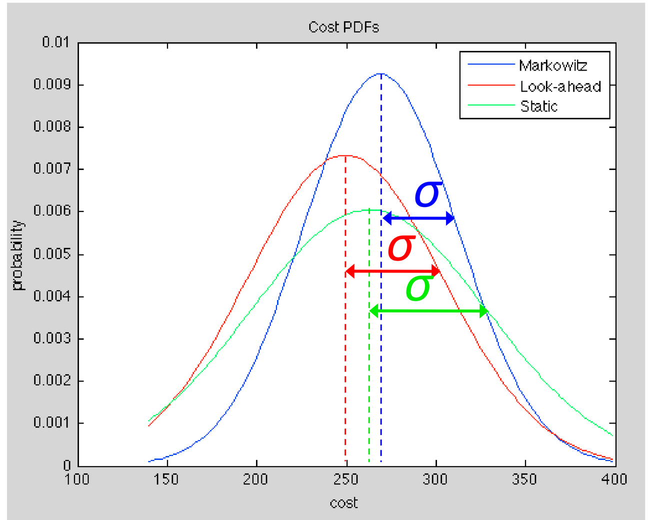


Demand optimizer

- **Three different optimization methods considered**
- **Static optimization**
  - Optimum as you go
  - Similar to on-off control
- **Look-ahead optimization**
  - Optimum over the whole 24-hour horizon
  - Model predictive control (MPC)
    : update/recalculate optimization as new info becomes available
- **Markowitz optimization**
  - Optimum including risk minimization
  - Minimizing the variance of the probabilistic cost

Simulation Results

- **Assumptions and settings**
  - No aggregation of different energy profiles of end-users
    : a single end-user
  - Price data taken from Zone DUQ in PJM
  - Simulated for the whole 2009
- **Cost probability distribution functions**
  - Calculated based on the variances of the hourly price and the purchase quantity at each hour
- **Markowitz optimization** shows the highest expected cost, but **the least risky profile**
  - Better performance expected with the actual real-time market purchase considered
- **Comparison of three different methods**
  : cost probability distribution functions



Conclusions and Future Work

- What is the **optimal portfolio**?
  - Depends on LSE's risk aversion/proneness
- **Future work**
  - Expanding this model to more diverse markets and less risky bilateral contracts
    - Question: How to deal with the different time scales
  - Including uncertainty of demand
  - Including the forecast errors of price and demand
    - How would the cost/profit actually turn out?
  - Designing tariffs/contracts with end-users
    : how much to charge end-users

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¶ Based on the working paper EESG WP-11

This work is partly supported by Robert Bosch LLC. The authors greatly appreciate their financial support.

Managing Bilateral Transactions in the Electricity Market

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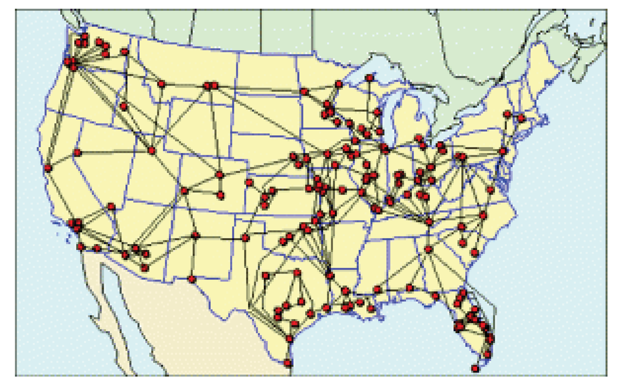
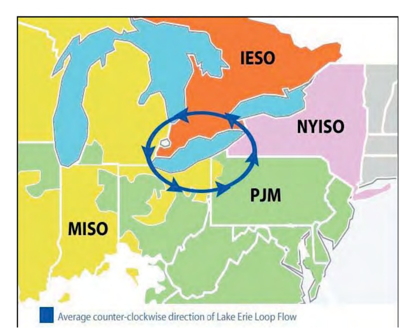
Motivation

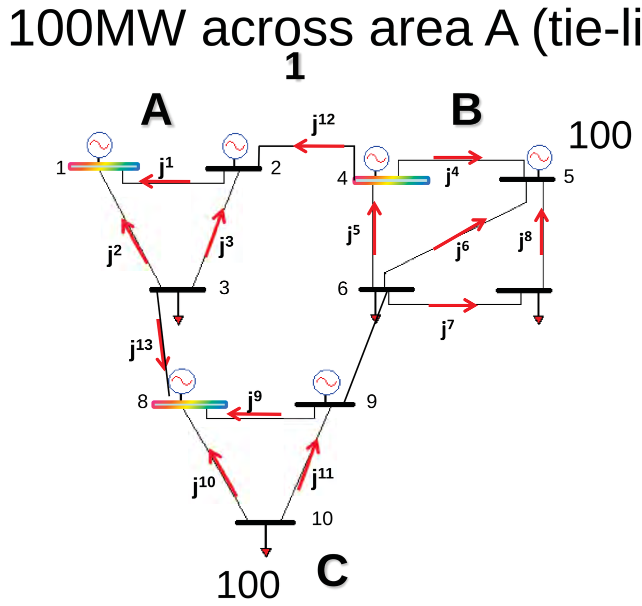
- Providing better insight in power system operation:
  - Where the power goes
  - Contributions to losses and congestion
- Managing electricity markets
  - Accounting for parallel flows
  - Accounting for bilateral transactions
  - Fair transmission loss pricing and charging for congestion
- Better power grid coordination
  - Enforcing contract paths
  - Eliminating circulating power
  - Enabling wheeling





Contract paths

- Bilateral transaction between generator 5 (area B) and load 10 (area C) for 100MW across area A (tie-lines j^{12} and j^{13})



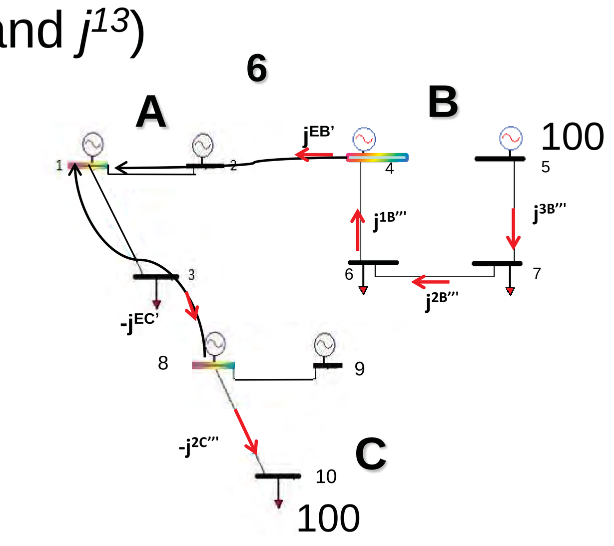
- $\min \| j^{alternate\_paths} \|^2$

st

KCL: $A_1^T * J^1 = J^1_{inj}$

KVL: $A_1^* V_1 = V_{1\_line}$

$j^{min\_contr} \leq j^{contr} \leq j^{max\_contr}$



- $\min \| j^{sN} \|^2$

st

KCL: $A_6^T * J^6 = J^6_{inj}$

$j^{min\_contr} \leq j^{contr} \leq j^{max\_contr}$

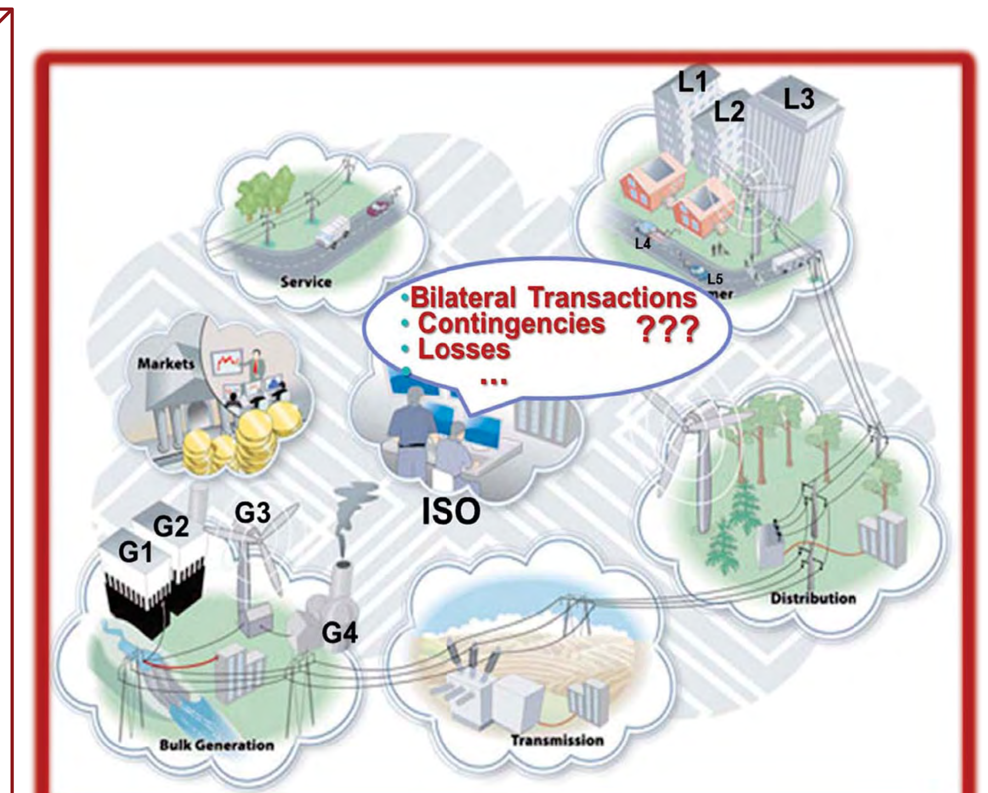
Applications

- Mechanism for accurate transmission pricing
- Enforcing contract paths using
  - Rescheduling of bilateral transactions
  - Line flow control devices
- Transformation of power networks into transportation network
- Adaptation of algorithms from graph theory to electrical networks
- Applicable to large interconnected networks – distributed algorithm based on model reduction

Main approach

- Bilateral transactions arranged directly between generators and loads
- Contract paths cannot be obeyed due to KVL
- Parallel flows occupy the lines not included in the contract path

- Main ideas:
  - Determine contributions of bilateral transactions to the line flows
  - Determine contributions of bilateral transactions to parallel flows
  - Design smart control that would maximize power flow through contract paths



Future Work

- Pricing mechanisms for congestion
- Integrating losses into the algorithm
- Adapting the algorithm for AC power flow

References

[1] H. H.Happ, 1980, *Piecewise Methods and Applications to Power Systems*. Wiley
[2] Felix F. Wu Ping Wei, Yixin Ni. Load flow tracing in power systems with circulating power. Electrical Power and Energy Systems, 24:807–813, 2002
[3] Lake Erie loop flow mitigation a report from NYISO, 2008.

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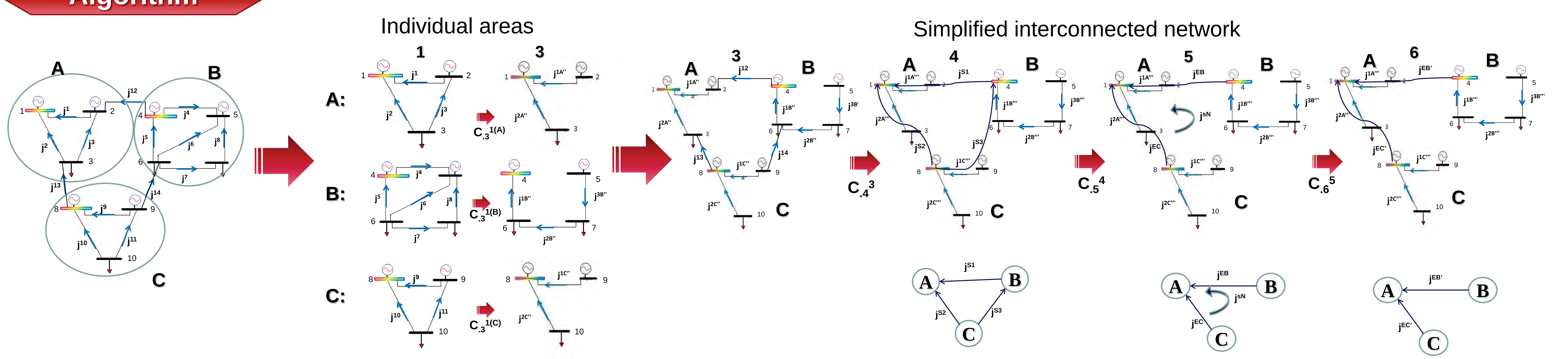
Algorithm



Bilateral Transaction Tracing

$$J^1 = C_{.3}^{1} * C_{.4}^{3} * C_{.5}^{4} * C_{.6}^{5} * J^6$$

Parallel Flow Tracing

$$V_5 = Z_{55} * J^5$$

$$\begin{bmatrix} V_{bilat\_trans} \\ 0 \end{bmatrix} = \begin{bmatrix} Z_{11} & Z_{12} \\ Z_{21} & Z_{22} \end{bmatrix} * \begin{bmatrix} J^{bilat\_trans} \\ J^{parallel\_flow} \end{bmatrix}$$

$$J^{parallel\_flow} = -Z_{22}^{-1} * Z_{21} * J^{bilat\_trans}$$

Energy Based Nonlinear FACTS Control

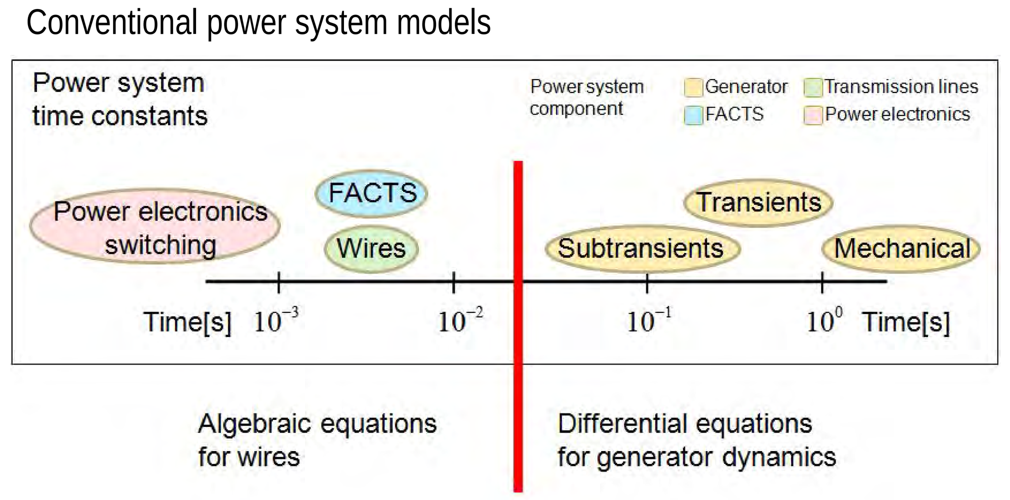
Miloš Cvetković (mcvetkov@andrew.cmu.edu) **and Marija Ilić** (milic@ece.cmu.edu)

Motivation

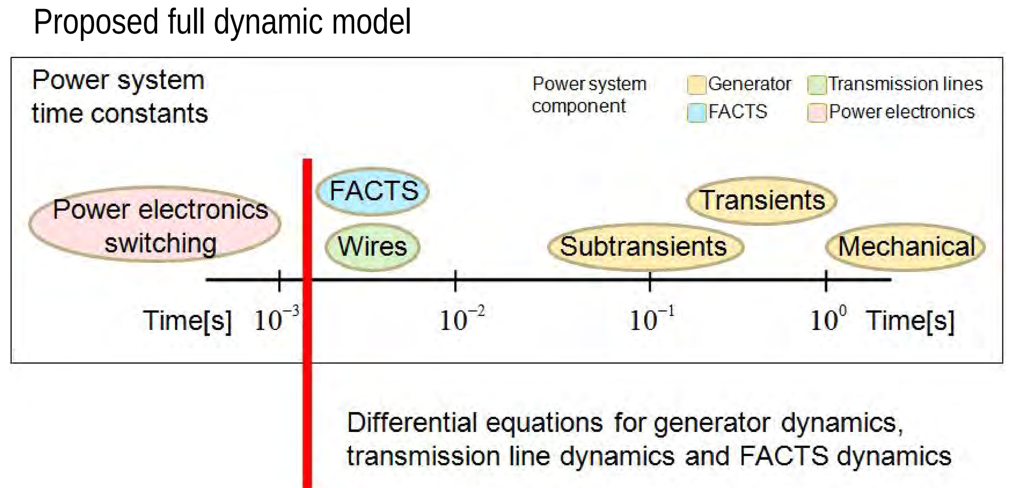
- **Transient stabilization** using FACTS has not been done in the past.
  - Systematic approach to control design on the system level still does not exist.
  - Existing FACTS control solutions are based on assumptions or simplifications of the model (DAE, dominant dynamics, no network dynamics, network reduction…).
- **Value** that FACTS have to the system in terms of stability is undetermined.
  - Dependence between critical clearing time, type of FACTS device and the size of its inductive and capacitive elements has not been determined yet.

Modeling

Conventional power system models

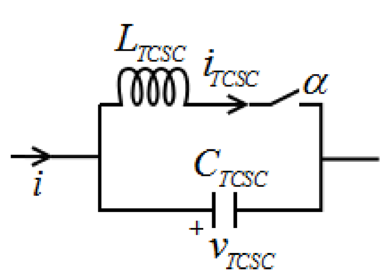


Proposed full dynamic model



- **ODE power system model** which captures **fast dynamics** of wires and FACTS devices is introduced.
- **Time varying phasors** are used to model network and FACTS dynamics.
- **TCSC** has been taken as a FACTS representative.

TCSC



Time domain representation

$$i - i_{TCSC} = C_{TCSC}\frac{dv_{TCSC}}{dt}$$

$$\alpha v_{TCSC} = L_{TCSC}\frac{di_{TCSC}}{dt}$$

Time varying phasor representation

$$\dot{V}_{TCSCD} = \frac{1}{C_{TCSC}}(I_D - I_{TCSCD}) + \omega V_{TCSCQ}$$

$$\dot{V}_{TCSCQ} = \frac{1}{C_{TCSC}}(I_Q - I_{TCSCQ}) - \omega V_{TCSCD}$$

$$\dot{I}_{TCSCD} = \frac{\alpha}{L_{TCSC}}V_{TCSCD} + \omega I_{TCSCQ}$$

$$\dot{I}_{TCSCQ} = \frac{\alpha}{L_{TCSC}}V_{TCSCQ} - \omega I_{TCSCD}$$

Component	State	Dynamic equation	Time scale
Generator	Stator current	$\dot{I}_G = A_1(\delta,\omega)I_G + B_1(\delta,\omega)i_G + C_1(\delta)V_B + D_1(\delta)V_F$	Fast
	Rotor currents	$\dot{i}_G = A_2(\delta,\omega)I_G + B_2(\omega)i_G + C_2(\delta)V_B + D_2V_F$	Medium
	Rotor angle	$\dot{\delta} = \omega$	Slow
	Frequency	$\dot{\omega} = m^{-1}(T_m - I_GV_B - D\omega)$	Slow
Transmission line	Bus voltage	$\dot{V}_B = C_e^{-1}(I_G \pm I_{TL} - I_L) + \omega V_B$	Fast
	Line current	$\dot{I}_{TL} = L_{TL}^{-1}(V_B - V_{TCSC} - R_{TL}I_{TL}) + \omega I_{TL}$	Fast
Load	Load current	$\dot{I}_L = L_L^{-1}(V_B - R_LI_L) + \omega I_L$	Fast
TCSC	Voltage	$\dot{V}_{TCSC} = C_{TCSC}^{-1}(I_{TL} - I_{TCSC}) + \omega V_{TCSC}$	Fast
	Current	$\dot{I}_{TCSC} = L_{TCSC}^{-1}V_{TCSC} + \omega I_{TCSC}$	Fast

Control

- **Energy based control** is using the **accumulated energy** in TCSC to stabilize large disturbances in the network.
- Energy function is defined as a sum of increments in accumulated energy of all devices.

$$\tilde{v} = \sum \tilde{v}_{gen} + \sum \tilde{v}_{trl} + \sum \tilde{v}_{facts} + \sum \tilde{v}_{load}$$

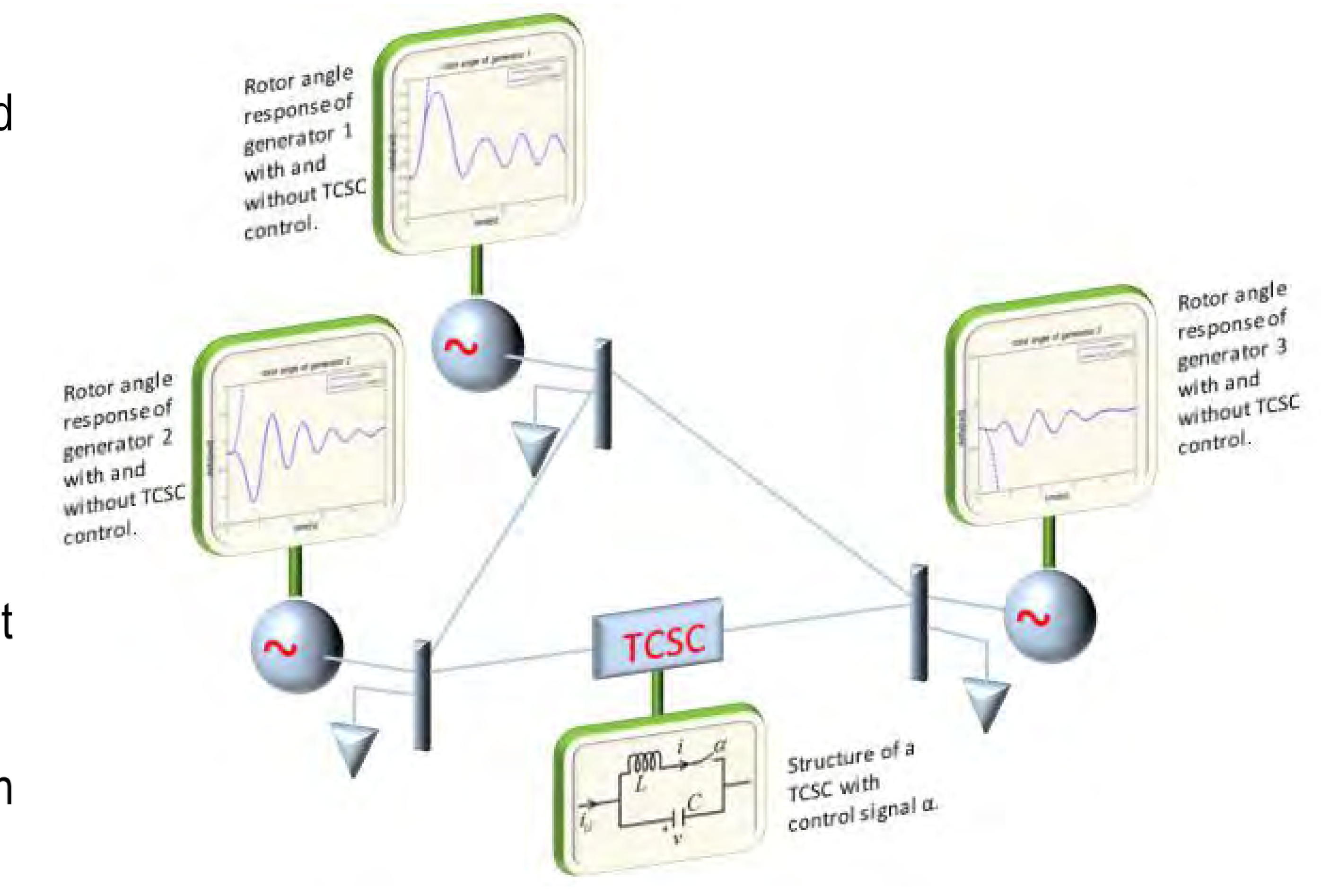
$$\dot{\tilde{v}} = \dot{\tilde{v}}_{acc} + \dot{\tilde{v}}_{io} + \dot{\tilde{v}}_{diss} + \dot{\tilde{v}}_{exch}$$

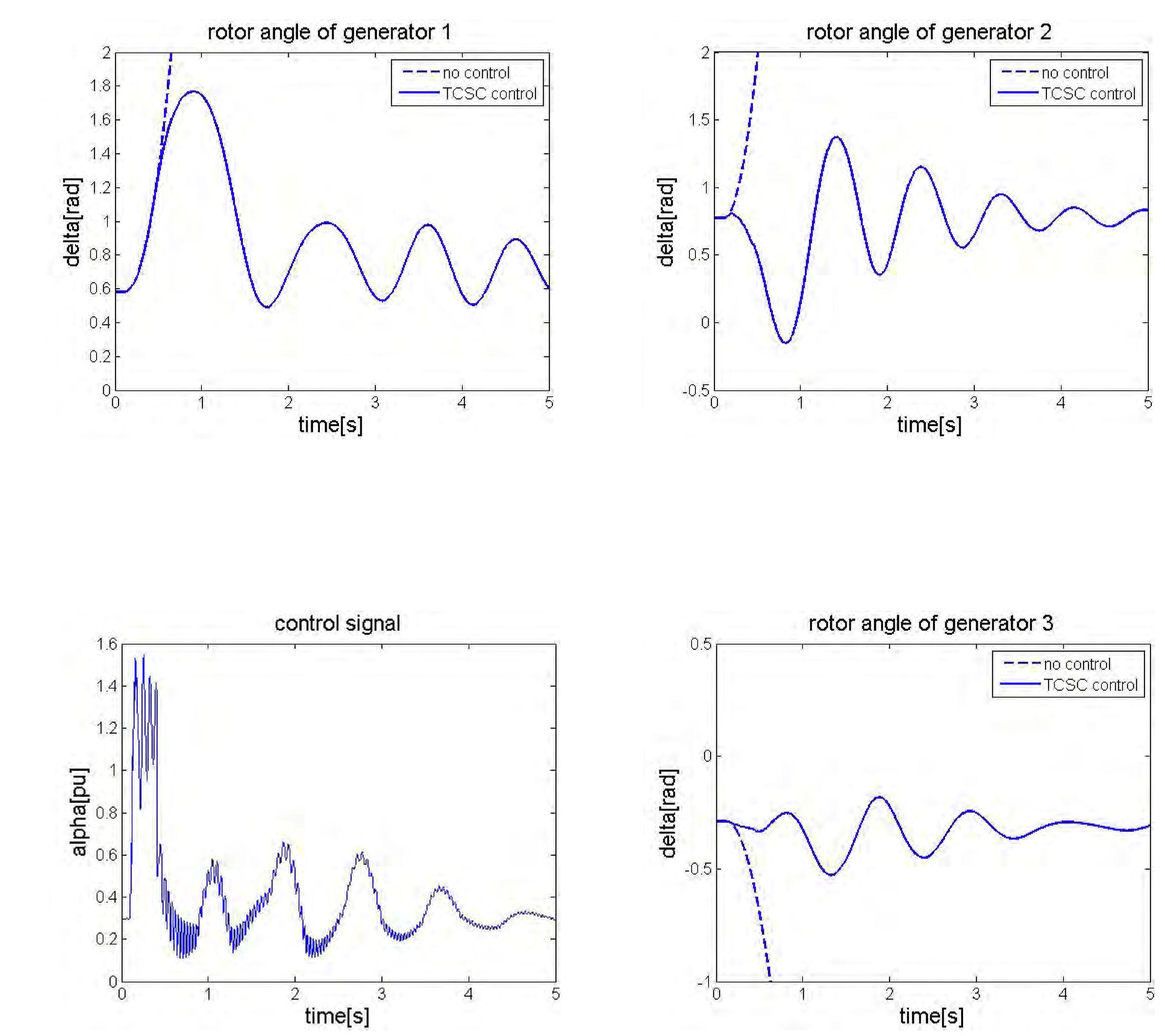
- $\dot{\tilde{v}}_{acc}$ is the rate of change of increment in energy accumulation.
- $\dot{\tilde{v}}_{io}$ is the rate of change of increment in the input/output energy injections.
- $\dot{\tilde{v}}_{diss}$ is the rate of change of increment in energy dissipation.
- $\dot{\tilde{v}}_{exch}$ is the rate of change of increment in energy exchange between devices in the system.

TCSC control

$$\alpha = \alpha_0 + K_p(\dot{\tilde{v}}_{io} - \dot{\tilde{v}}_{acc})$$

- A fault will create an imbalance in energy injection $\dot{\tilde{v}}_{io}$ which can be compensated by controlling energy accumulation $\dot{\tilde{v}}_{acc}$.
- Control performance has been tested on a three bus test case.





Conclusions & Future Work

Conclusions

- **A systematic approach** to modeling of power systems which allows an easy integration of new technologies has been established.
- **Energy based control** has shown satisfying performance in stabilization of large disturbances.

Future Work

- Investigation of other possible formulations of the control law.
- Modeling and evaluation of other FACTS devices.
- Modeling of large scale systems.

Acknowledgment

This work is supported by ABB and other SRC members through ERI program.

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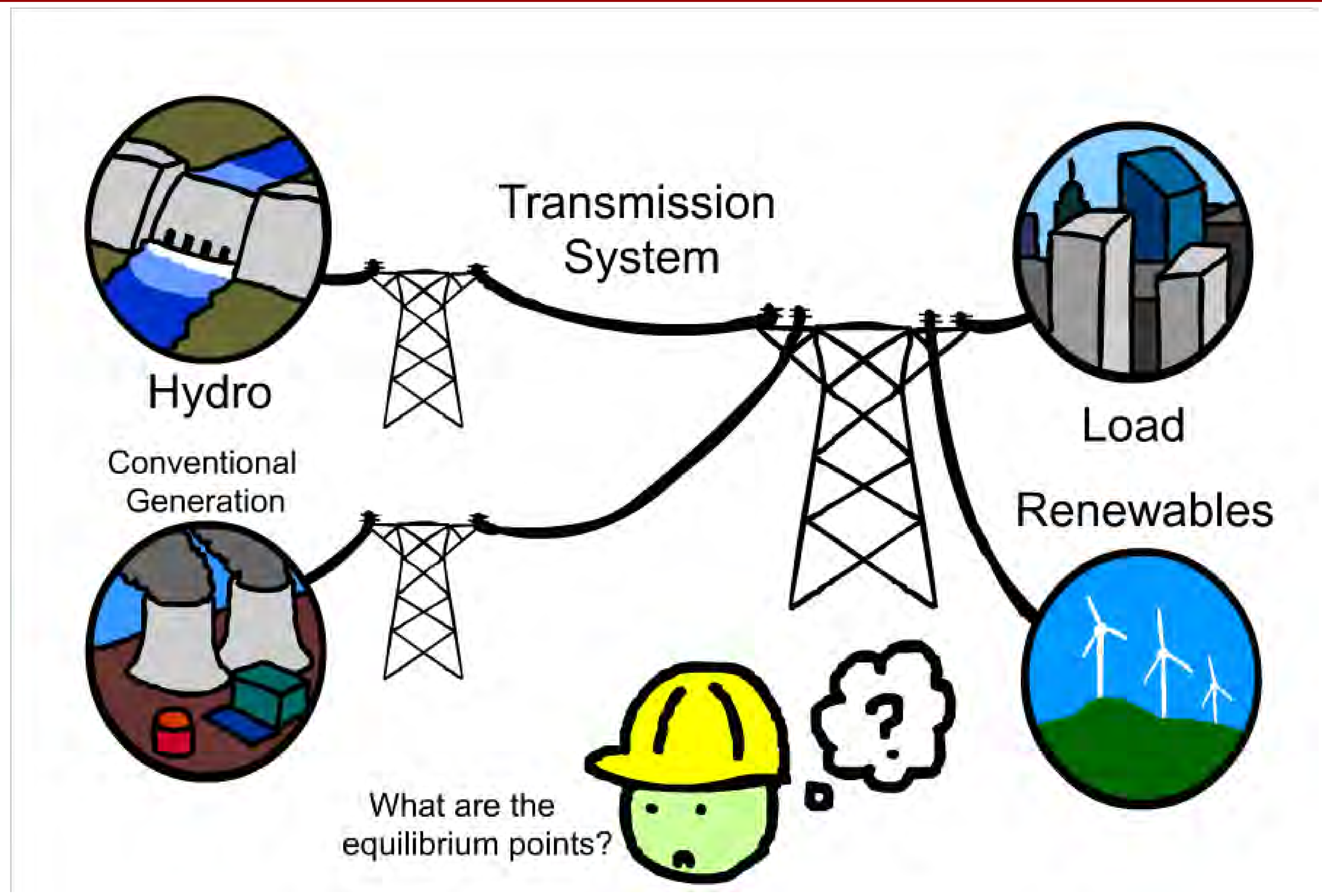
Towards Distributed Calculation of Equilibria in Electric Power Systems

Andrew Hsu and Marija Ilić

Motivation

- **Future energy systems more complex and dynamic with nonlinear components**
- **Dynamic analysis and control design frequently done with linearization around equilibrium points**
- **Is it possible to get real time calculation of equilibria in large power systems with many different components**

Future Power Systems



Proposed Method

- Set up problem as optimization problem with objective function reflecting equations dictating component behavior

$$minimize: f(x)=\sum_{e=1}^{E}\phi_e(x_e)$$

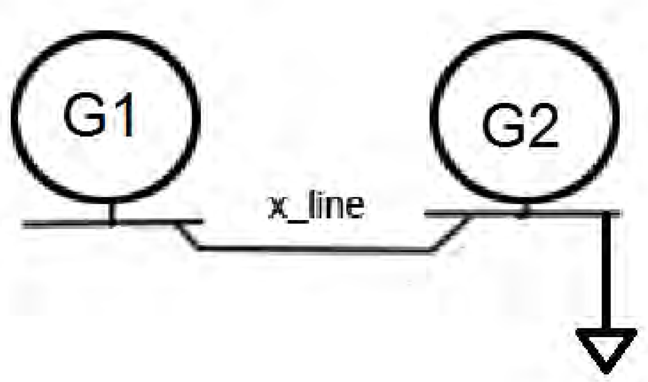
$$subject\ to: Ax=b$$

- Separate local and network variables: solve network step and then local step per iteration
- Based on equality-constrained Newton Method

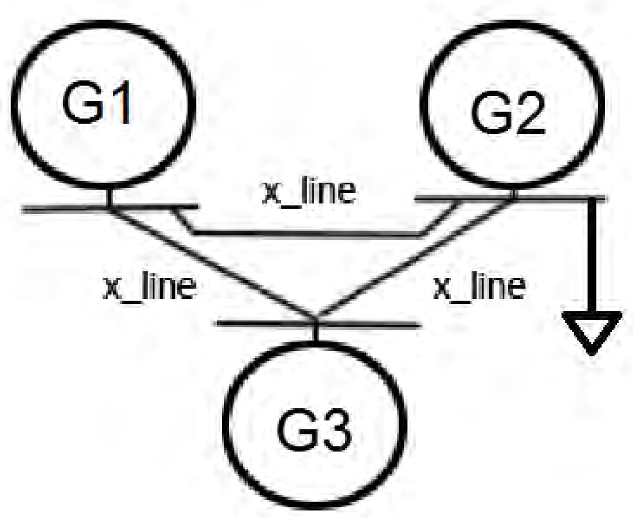
Real Power Decoupled

- **Real-Reactive power decoupled model**
- **System with conventional synchronous generators and constant power loads**
- **Examples shown for two and three bus systems**

Example : 2 bus and 3 bus



2 bus example



3 bus example

Example : 2 bus and 3 bus

Sys ref freq	1	**G ref freq2**	1
P Load	1	**Mech P 1**	0.5
G ref freq1	1	**Mech P 2**	0.5

	Solver	***Distr Solve***
Pe1	0.5000	0.5000
Pe2	0.5000	0.5000
Freq1	1.0000	1.0000
Freq2	1.0000	1.0000
Steps	2.0000	2.0000

2 bus example

Sys ref freq	1	**G ref freq3**	1
P Load	1.5	**Mech P 1**	0.5
G ref freq1	1	**Mech P 2**	0.5
G ref freq2	1	**Mech P 3**	0.5

	Solver	***Distr Solve***
Pe1	0.5000	0.5000
Pe2	0.5000	0.5000
Pe3	0.5000	0.5000
w1	0.7006	0.7006
w2	0.7006	0.7006
w3	0.7006	0.7006
Steps	2.0000	2.0000

3 bus example

Real Power Decoupled: Discussion

- **Requires some communication, but not inversion of a matrix which has length equal to the number of variables**
- **Real electrical power as network variable, other variables (frequency, mechanical power, control variables) are local**
- **Assumes voltage magnitude close to 1p.u. and voltage angle is small**

Future work

- **Real and Reactive power coupled method; does not assume voltage is a given value**
- **Method which takes advantage of measurements and communications**
- **Incorporation of unconventional components, such as renewable generation**

Acknowledgements

This work has been sponsored by SRC SGRC. (Semiconductor Research Corporation's Smart Grid Research Center).

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Automatic Generation and Demand Control : AGDC

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This work is supported by Energy Research Initiative (**ERI**), Semiconductor Research Corporation (**SRC**) for Smart Grid Research Centre (**SGRC**) at Department of Electrical and Computer Engineering, *Carnegie Mellon University*, Pittsburgh under **Task 2111.002**

Motivation

- Higher presence of wind energy in electric power systems, **requires more spinning reserves***
- Faster response needed to **compensate for non-zero mean deviations in wind power output (Time Scale varies)**
- Enable demand participation **to stabilize and regulate frequency**

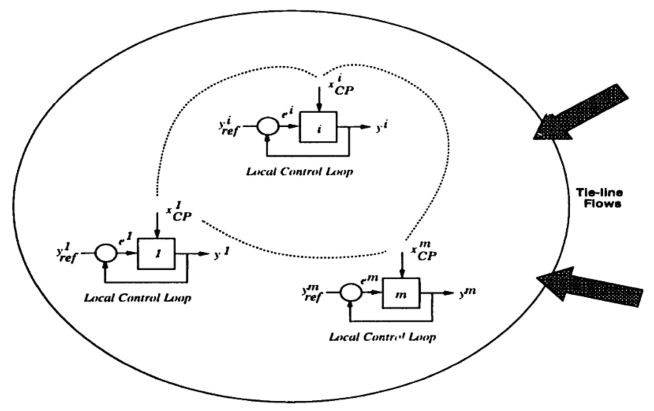
*Source: US Department of Energy,
http://www.ferc.gov/industries/electric/indus-act/reliability/frequencyresponsemetrics-report.pdf

Smart Loads & Demand Response

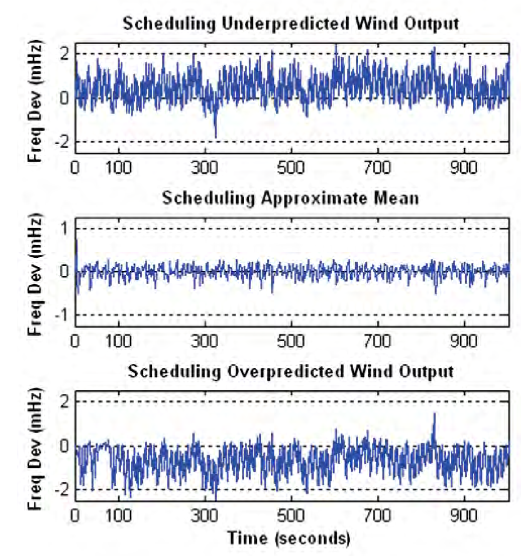
- **Inductive Loads** form large component of utility demand (***40-60%***). **Self Stabilizing** effect towards frequency offsets
- Power Regulation possible by embedding simple controllers and actuators into variable speed drives of different energy users **(Refrigerators, AC, Washer/Dryer)**
- **Distributed Energy Resources (Wind Turbines, Photovoltaic)** along with **Electric Vehicles and Battery Storage** can provide frequency response as well

Non-Dispatchable Wind

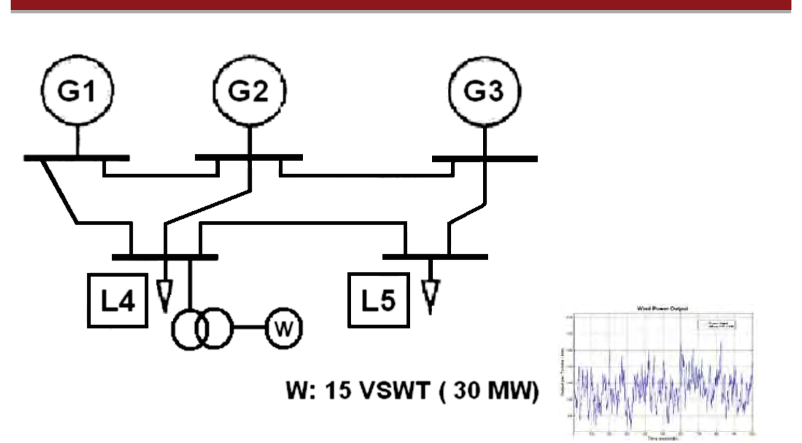
Conventional AGC



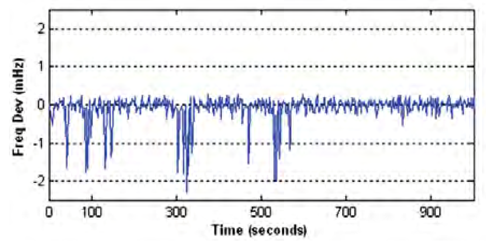
Violation of CPS



5-Bus System



Primary Reserves Activated



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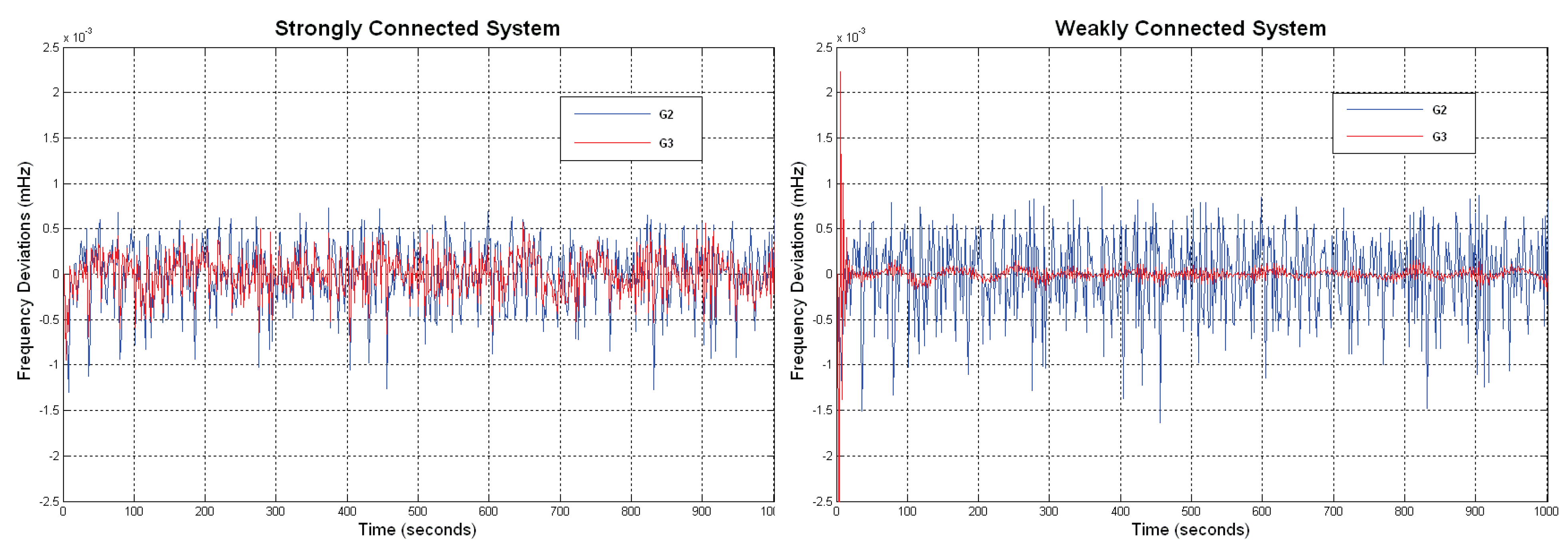
Effect of Location on Regulation Action

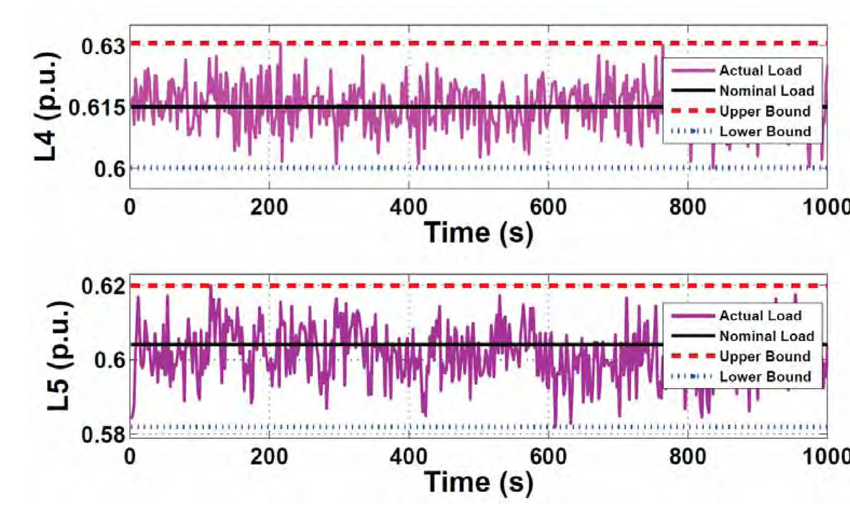


Automatic Generation & Demand Control

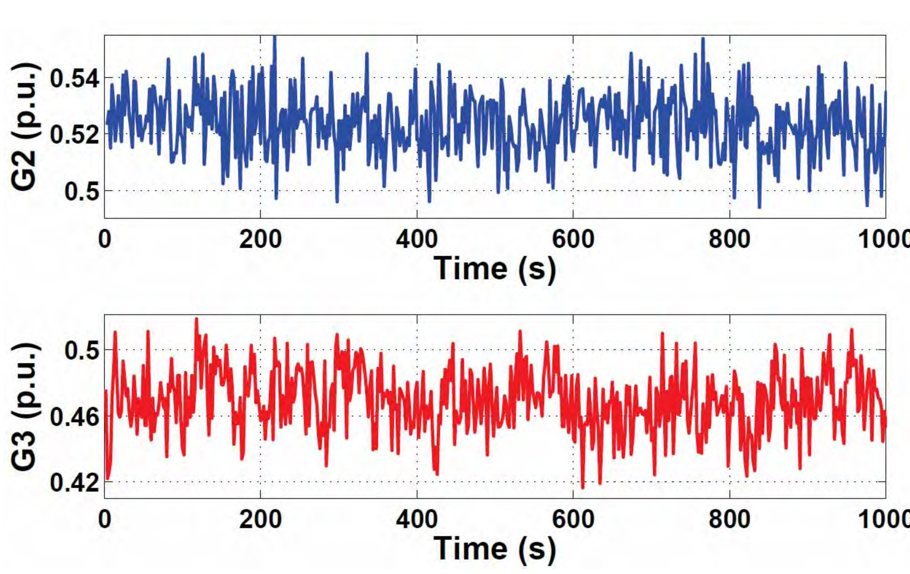
Distributed Approach

$$\omega_G \triangleq \begin{bmatrix} \omega_G^1 \\ \vdots \\ \omega_G^m \end{bmatrix}$$

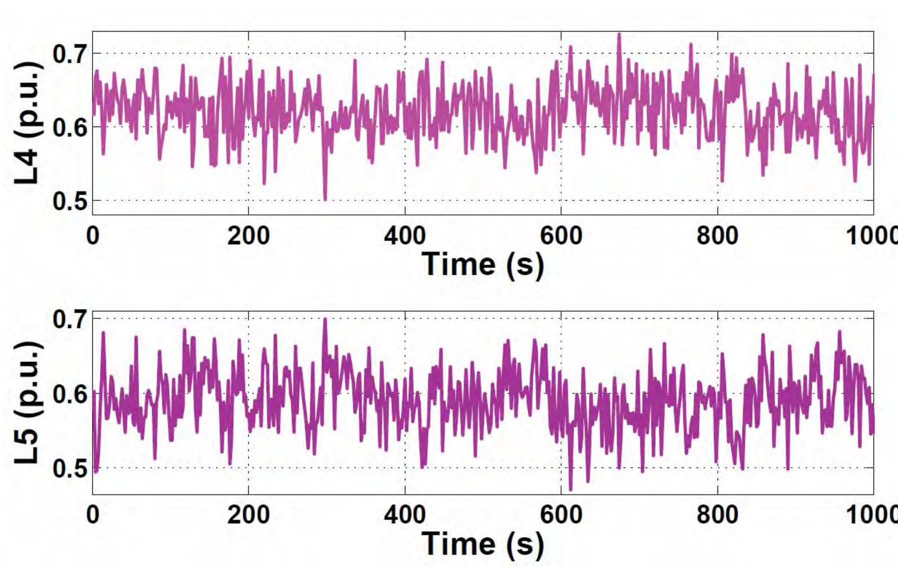
Proof of Concept

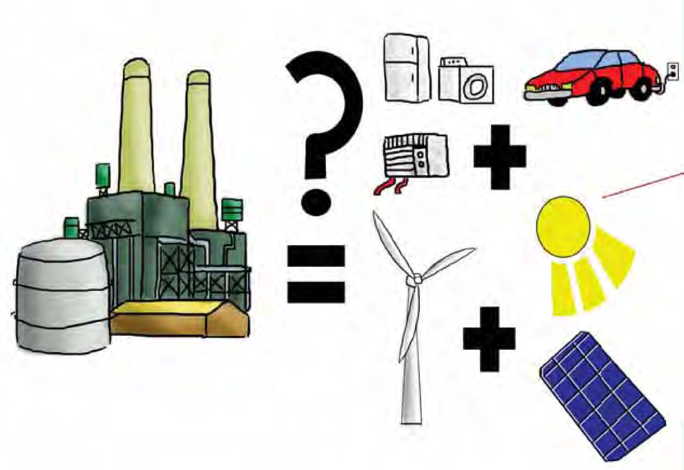


Governor Action



Demand Response



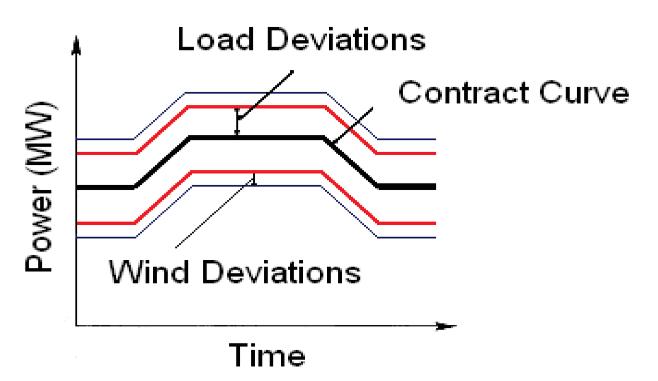


Demand Response required to offset need for one Natural Gas Plant ?

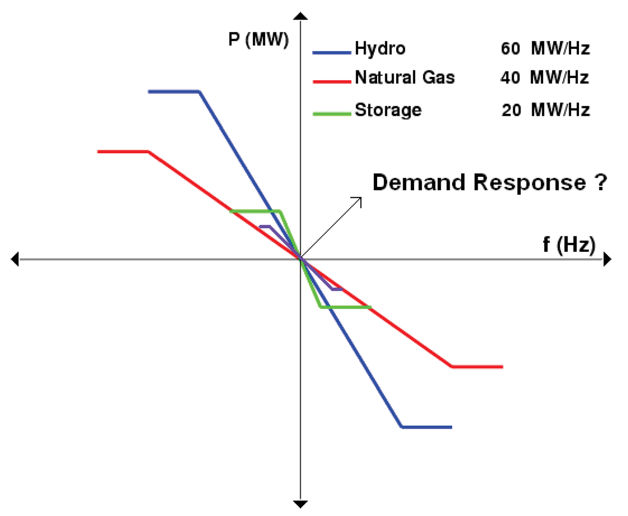
[1] *M. D. Ilić, N. Popli, J. Y. Joo, and Y. Hou*, "**A Possible Engineering and Economic Framework for Implementing Demand Side Participation in Frequency Regulation at Value**", accepted for IEEE Power Engineering Society General Meeting 2011"
[2] *M. D. Ilić, N Popli* "**Self-Stabilizing response of Loads towards Frequency Excursions: A Multi-Spatial approach**", EESG WP, CMU
[3] *M. Ilić and J. Zaborszky*, **Dynamics and Control of Large Electric Power Systems**

Differential Quality of Service (QoS)

Contract Curve Structure



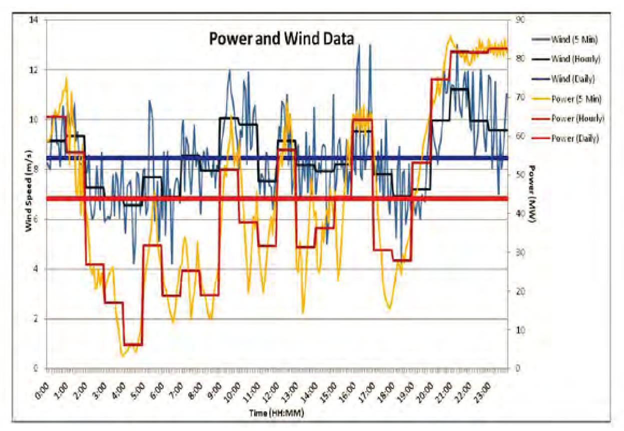
Bias Estimation



Technical Specifications

- Transmission/Locational Constraints
- Generator Ramp Rates, Load Characteristics
- Sensing & Communication

Next Steps ?



- Improving **Wind Prediction** Model
- Restructuring of **Ancillary Service Market** or Regulation Pricing Mechanism
- **Incentives** to encourage the use of Variable Speed Drive's Technology

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Distributed Control for Electric Power Systems to Enable the Integration of Renewable Energy Sources

Kyri Baker, Gabriela Hug, Xin Li

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Objective

To enable the integration of intermittent energy sources into the electric power grid by:

- Coordinating across control areas
- Using distributed predictive control
- Optimally utilizing available storage in overall system

Motivation

- The increasing unavailability of fossil fuels and their detriment to the environment encourages a push towards renewable sources. To increase the amount of renewable generation utilized, a method must be developed to more efficiently integrate this type of generation

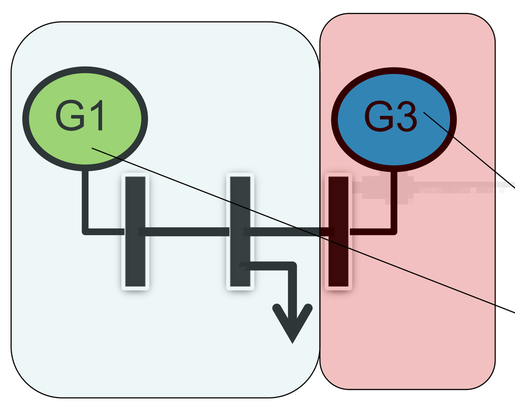
- Different devices in the power system which are located in separate control areas are usually not willing to fully exchange system data. The use of distributed control will account for this reality

-Predictive control will help limit the use of environmentally-unfriendly generation and ramp/up down of generators, resulting in an overall more efficient system

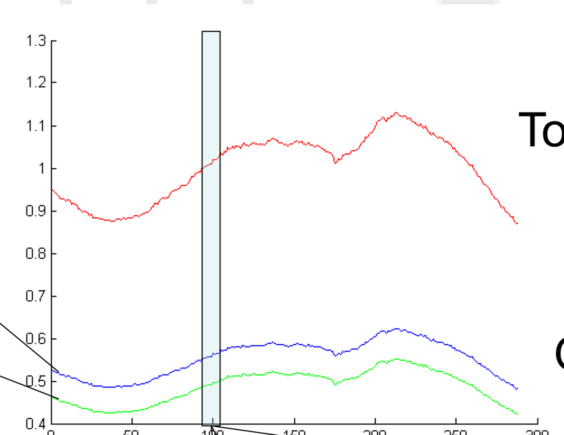
Progress / Next Steps

So far, we have implemented:

- System decomposition and optimization using Optimality Condition Decomposition (OCD) [1] , a method based on Lagrangian theory
- Optimization using an economic dispatch cost function
- Integration of a generic storage device



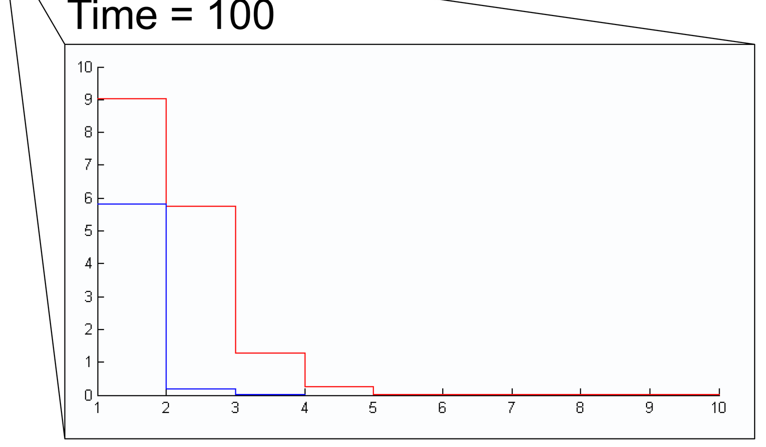
3-bus system



Total Load

Optimal Generation Levels

Time = 100



Convergence of Centralized System

Convergence of Decentralized System

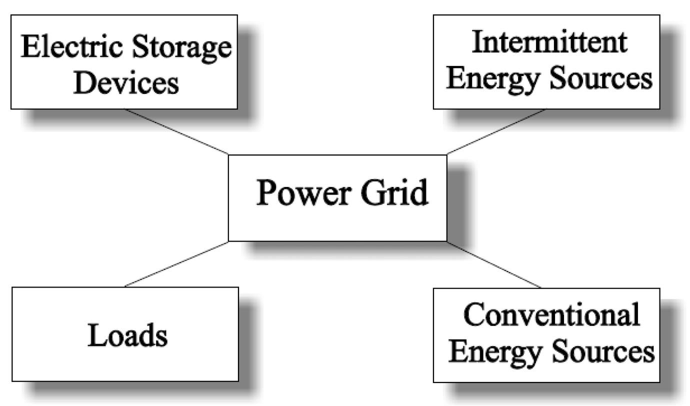
- Next Step: Predictive control, move to larger scale systems

Approach

System Objective and Constraints

-Objectives:

- Minimize cost of generation
- Maximize use of renewable sources
- Minimize use of backup generators
- Minimize ramp up/down of generators

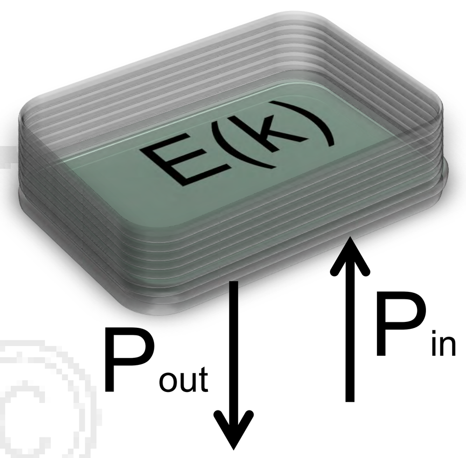


-Subject to:

- Physical power flow constraints
- Storage limits, power generation limits

Storage Devices

- Helps integrate sources which are intermittent
- Excess generated energy will be stored instead of curtailed
- Allows optimal usage of available transfer capacity



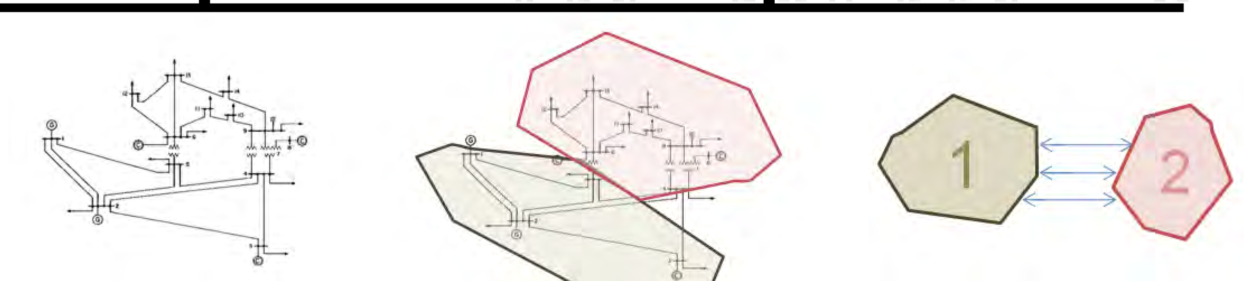
$$E(k+1) = E(k) + \alpha*T*P_{in} - T*P_{out}/\alpha$$

$$P_{in}*P_{out} = 0$$

α = conversion factor

T = time scale

System Decomposition and Optimization



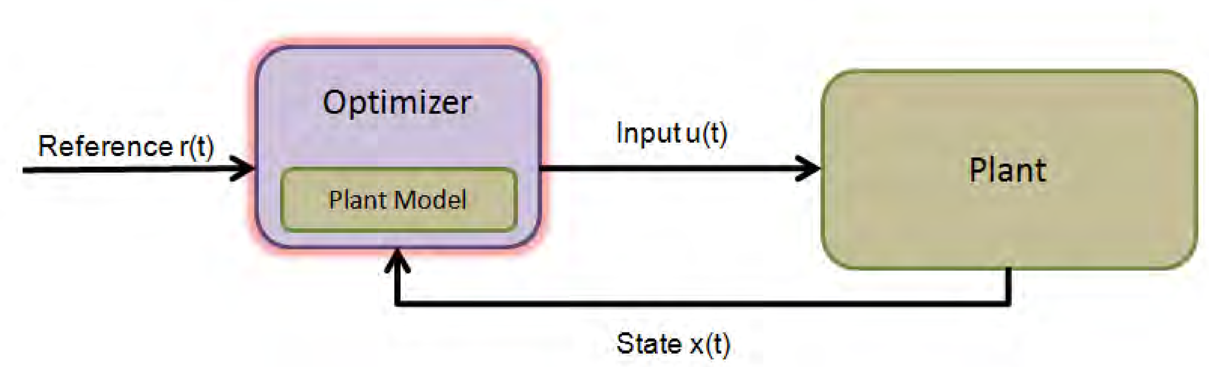
IEEE14-bus System

Split into Subareas

Communication between areas

-Using Optimality Condition Decomposition[1] to split the overall optimization into subproblems
- Iteratively optimize each subproblem independently using Newton-Raphson steps
- After optimal solution is reached for each subproblem, the problems exchange variable data

Model Predictive Control



- Uses a model of the system to optimize over a time horizon [2]
- Helps answer when to use storage, backup generation, load control, etc. based on load forecasts and wind generation predictions
- MPC is a computationally intensive and slow algorithm to use on a large power system; decomposition will alleviate issues with this

References:

[1]: F. Nogales, F. Prieto, and A. Conejo, "A decomposition methodology applied to the multi-area optimal power flow problem," *Annals of Operations Research, vol. 120, pp. 99–116, 2003.*

[2]: J.M. Maciejowski. *Predictive Control. Prentice Hall, 2002.*

Carnegie Mellon

Optimal Usage of Transmission Capacity with FACTS Devices to Enable Wind Power Integration

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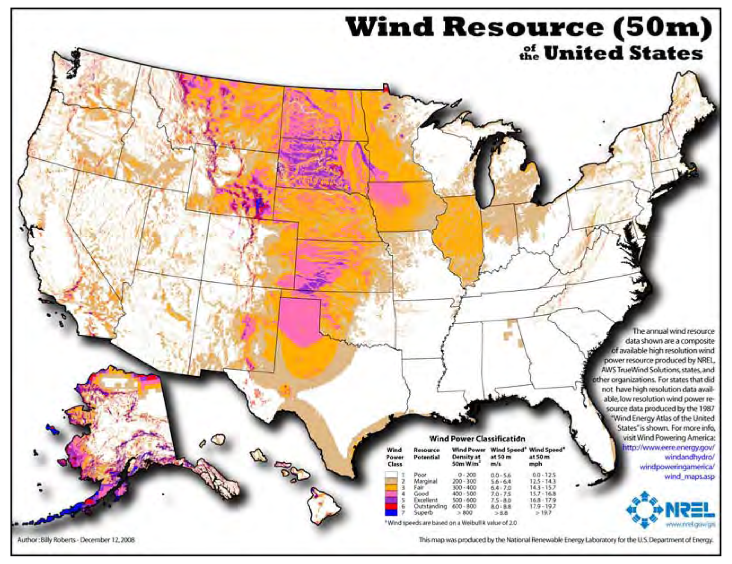
Motivation

❖ Accelerated Integration of Wind Energy Resources

❖ Challenges



Class	Potential	Density (W/m²)	Wind Speed (m/s)
1	Poor	0-200	0.0-5.6
2	Marginal	200-300	5.6-6.4
3	Fair	300-400	6.4-7.0
4	Good	400-500	7.0-7.5
5	Excellent	500-600	7.5-8.0
6	Outstanding	600-800	8.0-8.8
7	Superb	>800	>8.8

- Areas with high availability of wind (mostly central US) and demand centers (East and West coast) are distinct
- Limited transfer capacity of the transmission network in central US

❖ Possible Solutions

- Upgrading the current transmission system
  - High cost
- Using FACTS devices to influence voltages and power flows
  - Allowing better usage of the existing transmission system
  - Allowing quick adjusting to the power flows in the system

Main Idea

❖ Problems

- How to manage congestion in the network under various generation and load profiles
- How to deal with the high variability of the wind power resulting in varying power flows in transmission network

❖ Objective

- **Developing a scheme which will determine the optimal settings of the FACTS devices with respect to loading of transmission system**

❖ Approaches

- ***Centralized approach***
  - A central controller
  - Based on the Optimal Power Flow calculations
  - Information of the entire system needed
- ***Decentralized approach***
  - Local controller for each FACTS device
  - Based on a limited amount of local measurements
  - Communication between the measuring devices and controller needed

Decentralized Approach

❖ Structure

- Offline simulation for training purpose
- Online decision making

❖ Offline Simulation

- Under various generation and load scenarios
- Solving optimization problem to get the optimal settings
- Finding a function: ***optimal setting = f(local measurements)***

❖ Online Decision Making

- Function stored in the controller of the FACTS device
- Measurements of the active power flows, currents and voltages
- Setting of the FACTS device at current state

Offline Simulation

❖ Optimization Problem Formulation

- ***Control variable***
  - Setting of the FACTS device X_{TCSC} or $\eta_{TCSC} = \frac{X_{TCSC}}{X_{Line}}$
- ***Objective function***
  - Maximizing the minimum value of the capacity margin

$$\max \ (\min \ (P_{margin,ij})), \quad where \ P_{margin,ij} = \frac{F_{ij}^{\max} - |P_{ij}|}{F_{ij}^{\max}}$$

- ***Constraints***
  - Power flow equations $P_{G,i} - P_{L,i} - \sum_j P_{ij} = 0, Q_{G,i} - Q_{L,i} - \sum_j Q_{ij} = 0$
  - Model of the loads $P_{L,k} = P_{L,k}^0 + \Delta P_{L,k}, PF_{L,k} = \text{constant}$
  - Capacity limits of the transmission line $|P_{ij}| \le F_{ij}^{\max}$
  - Limits of the settings

$$\max(X_{TCSC,\min}, -0.9X_{Line}) \le X_{TCSC} \le \min(X_{TCSC,\max}, 0.4X_{Line})$$

❖ Determining Key Measurements

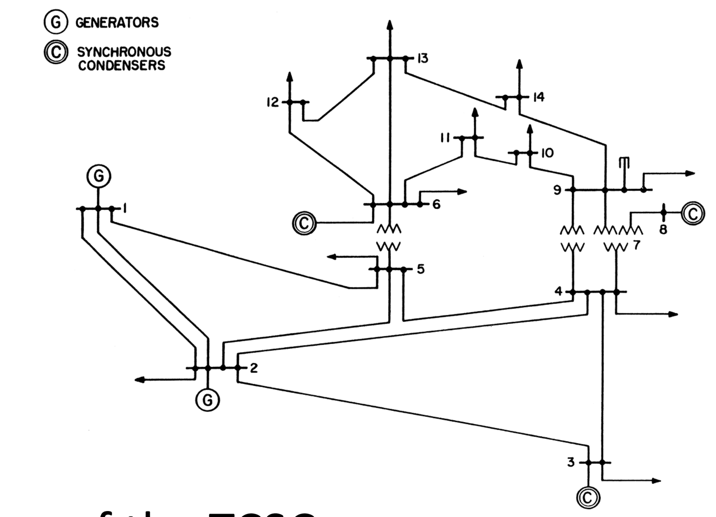
- Active power flow through the transmission lines
- Current magnitude of the transmission lines
- Voltage magnitude and angle at buses

❖ Regression Analysis

- Polynomial fitting

Preliminary Results

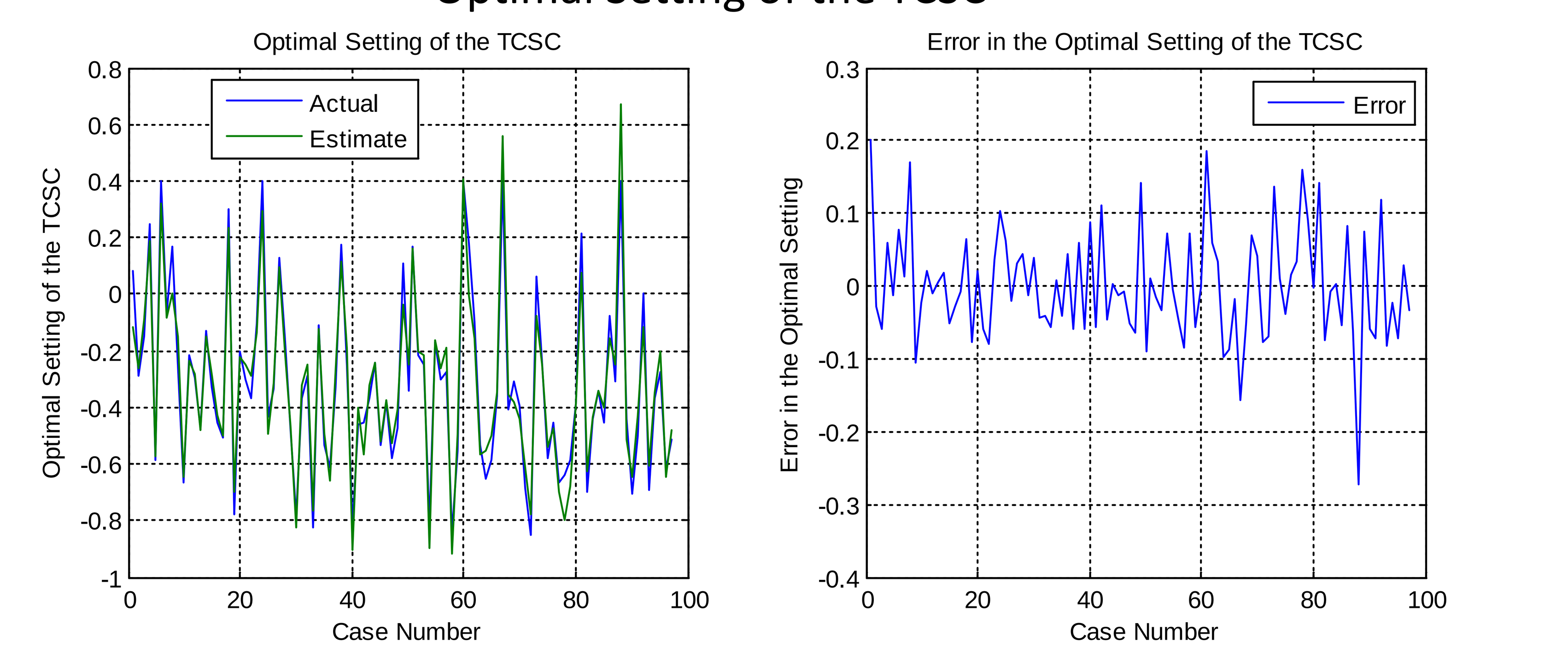
❖ System Setup



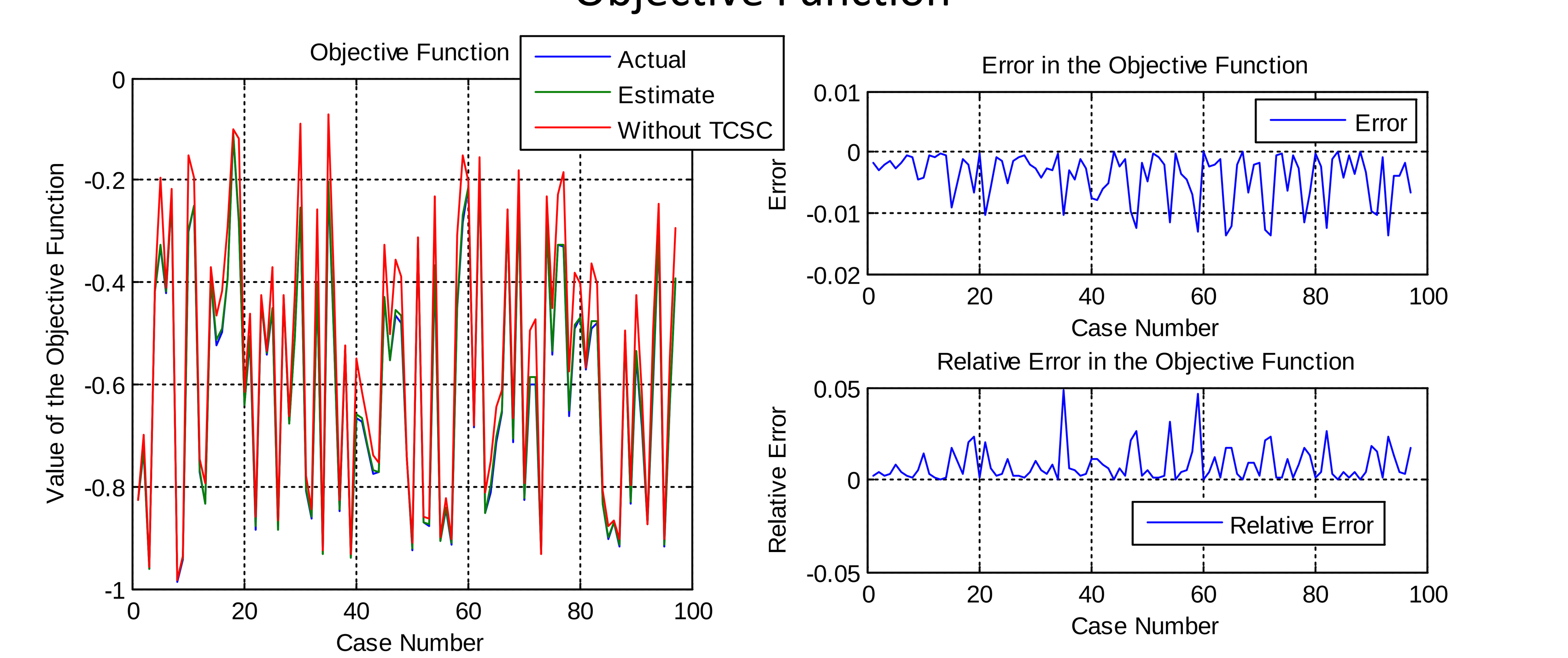
- IEEE 14-bus system
- Wind generator at Bus 2
- TCSC in Line 1-2
- Load center on north side

❖ Simulation Results

Optimal Setting of the TCSC



Objective Function



Conclusions and Future Work

❖ Conclusion

- Promising preliminary results for the decentralized approach to determine the optimal settings of the FACTS devices

❖ Future Work

- Different locations for the FACTS devices
- Including the setting of the FACTS devices at current state also as a measurement
- Further testing with different cases for training and online simulation
- Larger system

Electric Energy EESG Systems Group

Electrical & Computer ENGINEERING

Real-Time Control of Energy Storage Devices in Future Electric Power Systems

Dinghuan Zhu, Gabriela Hug-Glanzmann

Electric Energy Systems Group, Electrical and Computer Engineering

Motivation

- More challenging power balancing mechanism due to the high intermittency and variability of renewable resources
- Continuous development of energy storage technologies

Possible energy storage applications:

➢ **Integration of renewable generators**, frequency regulation, **generation/transmission deferral**, tie-line flow control and ramping rate control for microgrids

Control Principle

Multi-Step Optimization

A multi-step optimizer predicts the future influence of control inputs on the system using a model of the system.

$$\min \sum_{k=0}^{N-1} f_k(X,U)$$
$$\text{s.t.}\quad g_k(X,U)=0,\ k=0,\cdots,N-1$$
$$h_k(X,U)\le 0,\ k=0,\cdots,N-1$$
$$\text{where}\quad X=[x(t),\cdots,x(t+N-1)]^T$$
$$U=[u(t),\cdots,u(t+N-1)]^T$$

N: look-ahead horizon;

t: current time step.

➢ **Control procedure:**

1) At time step t, the optimization problem is solved and only the first control step $u(t)$ is applied to the system,
2) The state of the system at the next time step is determined by new measurements. The look-ahead horizon is moved by one. The optimization is redone for the shifted horizon.

Model of Storage Devices

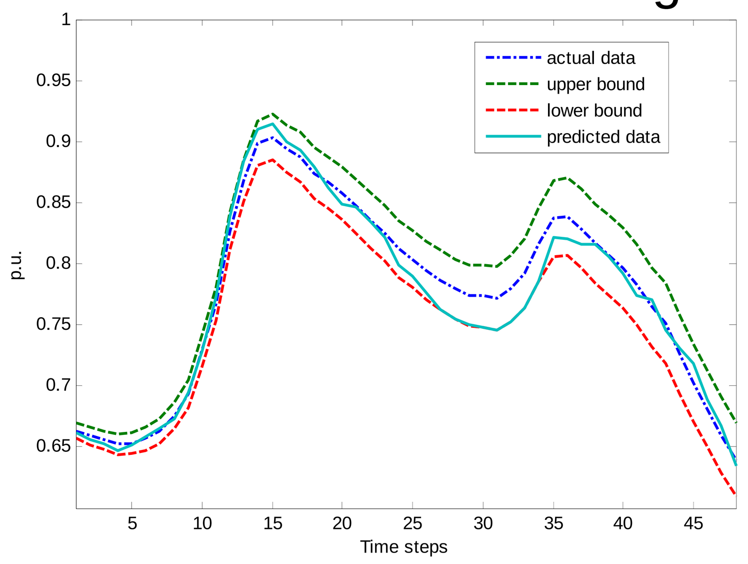
State of Charge (SOC), power output capability, conversion losses and standby losses are captured by the generic model.

$$E_S(k+1)=E_S(k)-\eta\cdot P_S(k)\cdot T-\rho\cdot E_S(k)$$
$$\eta=\begin{cases}\eta_{out}=1/\mu, & P_S(k)\ge 0\\ \eta_{in}=\mu, & P_S(k)<0\end{cases}$$
$$P_S^{\min}\le P_S(k)\le P_S^{\max}$$
$$0<\mu\le 1$$

- $E_S(k)$, $P_S(k)$: energy level and power injection of the storage;
- η: conversion factor;
- μ: efficiency of the energy conversion process;
- ρ: standby losses.

Model of Uncertainties

- Uncertainties in renewable energy and load prediction
- Mean Absolute Percentage Error (MAPE) in power systems



$$(1-e(k))\cdot P(k)\le \hat{P}(k)\le (1+e(k))\cdot P(k)$$
$$0\le e(k)\le 1$$

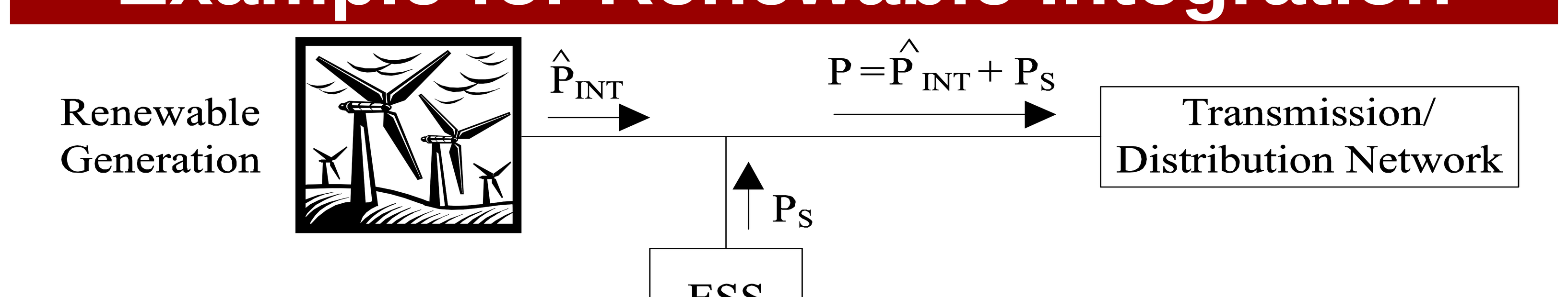
➢ $P(k)$, $\hat{P}(k)$, $e(k)$: actual, predicted and MAPE values for a certain forecast variable.

- Uncertainty also arises in the duration of a discrete time step. Original time step size T is evenly divided into n subintervals. Assumptions:
  1) The average of n values remains the same as the previously predicted value for the time step;
  2) The empirical Mean Absolute Deviation (MAD) for these n values is φ given in percentage.

$$\hat{P}(k)=\frac{1}{n}\cdot\sum_{k=0}^{n-1}\hat{P}(k,i);$$
$$(1-\varphi)\hat{P}(k)\le \hat{P}(k,i)\le (1+\varphi)\hat{P}(k),\ \forall i$$

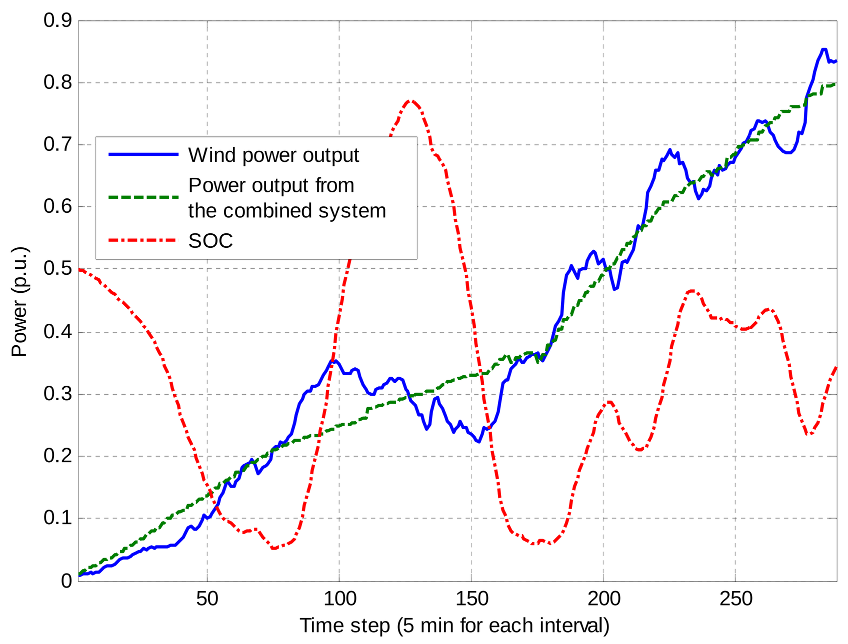
$\hat{P}(k,i)$: predicted value for the forecast variable in the *(i+1)th* subinterval of time step k.

Example for Renewable Integration



$$\min_{P(k),P_S(k)} \sum_{k=0}^{N-1}[(P(k)-P(k-1))^2+\alpha P_S^2(k)+\beta E_S^2(k,2)]$$
$$E_S(k,i+1)=E_S(k,i)-\eta\cdot P_S(k)\cdot\frac{T}{2}-\frac{\rho}{2}\cdot E_S(k)$$
$$E_S(k+1,0)=E_S(k,2)$$
$$\hat{P}_{INT}(k)+P_S(k)=P(k)$$
$$\overline{E}_S(k,1)=E_S(k,1)+\eta_{in}\cdot\frac{\varphi}{1-e(k)}\cdot\hat{P}_{INT}(k)\cdot\frac{T}{2}$$
$$\text{s.t.}\quad \underline{E}_S(k,1)=E_S(k,1)-\eta_{out}\cdot\frac{\varphi}{1-e(k)}\cdot\hat{P}_{INT}(k)\cdot\frac{T}{2}$$
$$\overline{E}_S(k,2)=E_S(k,2)+\eta_{in}\cdot\frac{e(k)}{1-e(k)}\cdot\hat{P}_{INT}(k)\cdot T$$
$$\underline{E}_S(k,2)=E_S(k,2)-\eta_{out}\cdot\frac{e(k)}{1-e(k)}\cdot\hat{P}_{INT}(k)\cdot T$$
$$E_S^{\min}\le\overline{E}_S(k,i+1),\underline{E}_S(k,i+1)\le E_S^{\max}$$
$$P_S^{\min}\le P_S(k)\le P_S^{\max}$$

Simulation system setup:
N = 6 hours;
T = 10 min;
$P_S^{\max}$ = 1.0 p.u.;
$E_S^{\max}$ = 0.3 p.u.hour;
MAPEs for wind = 10% - 17%;
MAD = 10%.



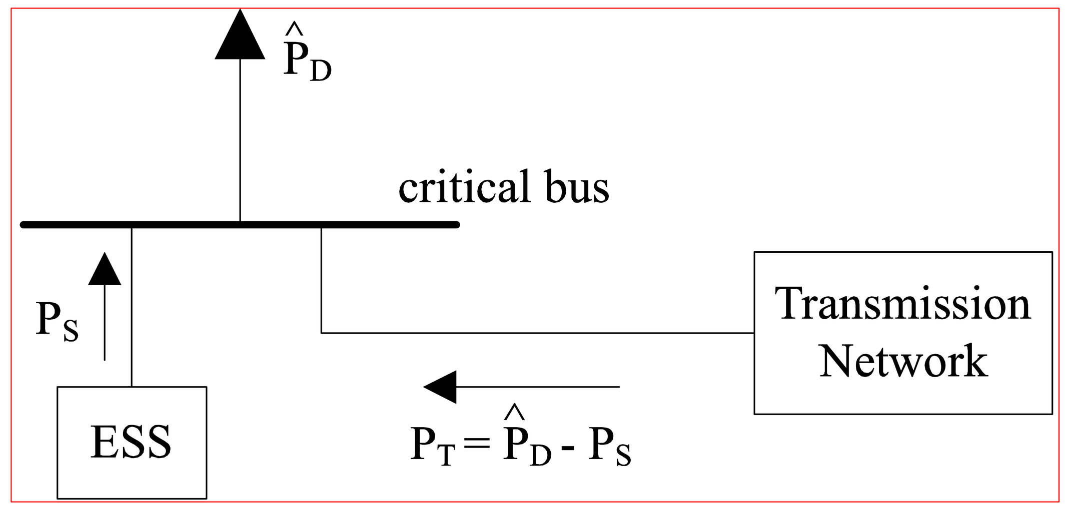
Objectives:

(-) fluctuations in wind power;

(-) conversion losses of ESSs;

(-) energy reservation of ESSs.

Example for G/T Deferral



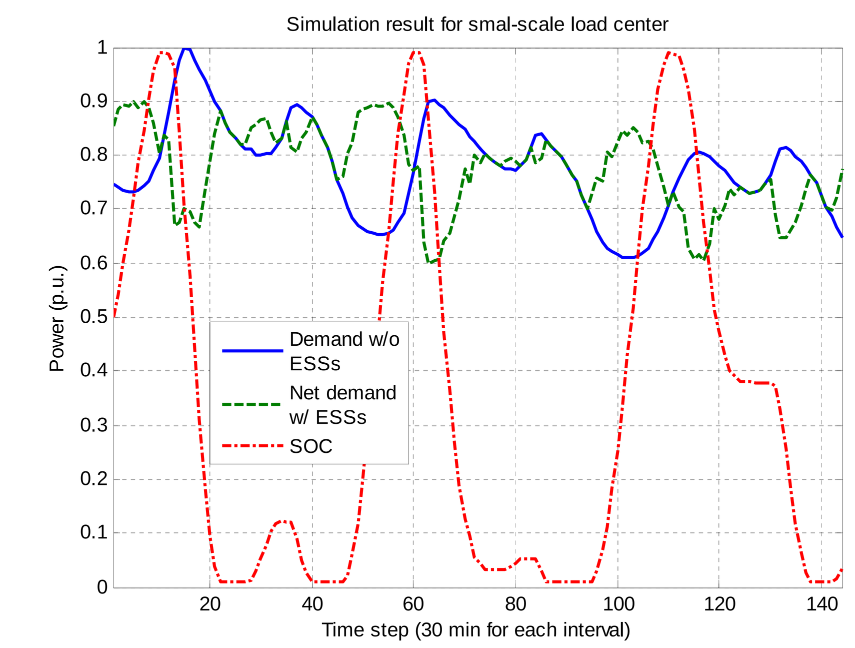
Objectives:
(-) ESS operational cost;
(-) ESS conversion losses.

$$\min_{P_S(k)} \sum_{k=0}^{N-1}[(\hat{P}_D(k)-P_S(k))\cdot f(\hat{P}_L(k)-P_S(k))+\alpha P_S^2(k)]$$
$$E_S(k+1)=E_S(k)-\eta\cdot P_S(k)\cdot T-\rho\cdot E_S(k)$$
$$E_S^{\min}\le E_S(k+1)\le E_S^{\max}$$
$$P^{\min}\le\hat{P}_D(k)-P_S(k)\le P^{\max}$$
$$\text{s.t.}\quad P^{\min}\triangleq P_T^{\min}+\frac{e(k)}{1-e(k)}\cdot\hat{P}_D(k)$$
$$P^{\max}\triangleq P_T^{\max}-\frac{e(k)}{1-e(k)}\cdot\hat{P}_D(k)$$
$$P_S^{\min}\le P_S(k)\le P_S^{\max}$$

Simulation system setup:
N = 24 hours;
T = 30 min;
$P_S^{\max}$ = 0.3 p.u.;
$E_S^{\max}$ = 1.2 p.u.hour;
$P_T^{\max}$ = 0.9 p.u.
MAPEs for load = 1% - 5%.

Assumptions: 1) demand curve at the load center is proportional to the one of the overall system; 2) price function f is a quadratic function of the total system demand for illustration purpose.

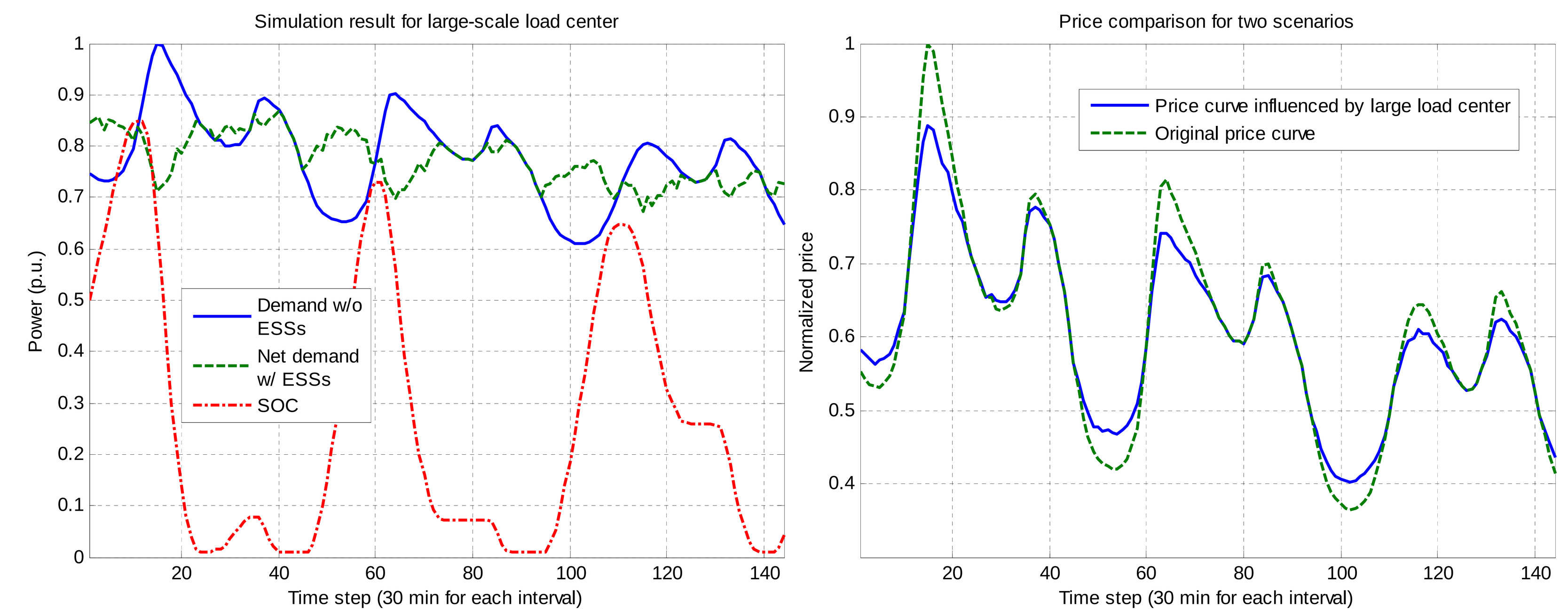
➢ **Scenario 1 (small-scale load center)**



- Price-taker;
- More use of storage;
- Steep price curve.

➢ **Scenario 2 (large-scale load center)**

- Price-maker;
- Less use of storage;
- Flat price curve.



Electric Energy EESG Systems Group

Electrical & Computer ENGINEERING

A Monte Carlo Framework for Probabilistic Distribution Power Flow

Toward building a supercomputing center for distribution substation

Tao Cui and Franz Franchetti

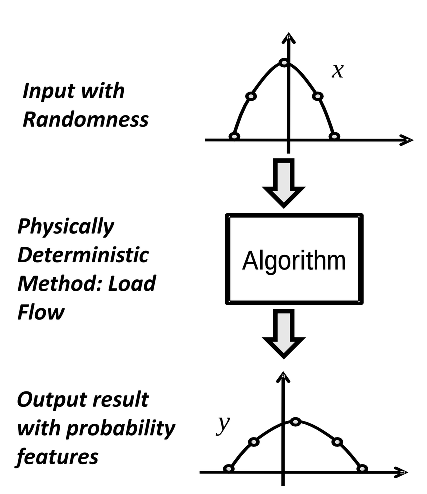
Email: tcui@ece.cmu.edu

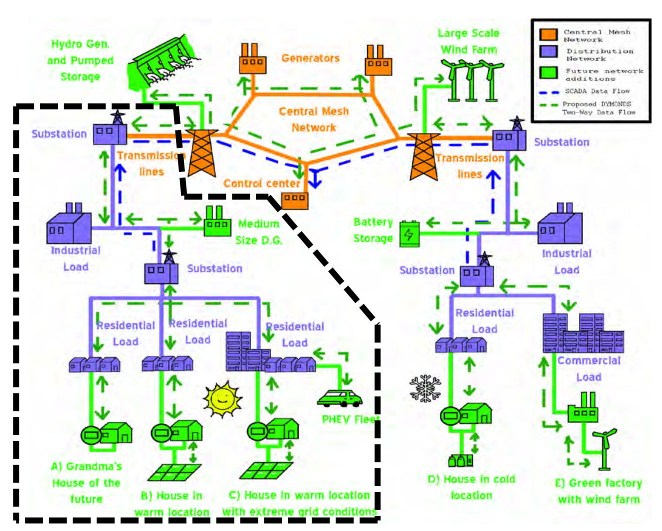
EESG Cyber Phycial System Project, Department of Electrical and Computer Engineering

Motivation and Background

❖ Problems from Power System

- Uncertainties in electric power distribution system:
  - Wind power, DG, PHEV, responsive load, etc.
  - AMI, Smart metering provide fine grain measurement profile.
  - Probabilistic power flow: report “worst case” , “confident interval” and result with probability features.



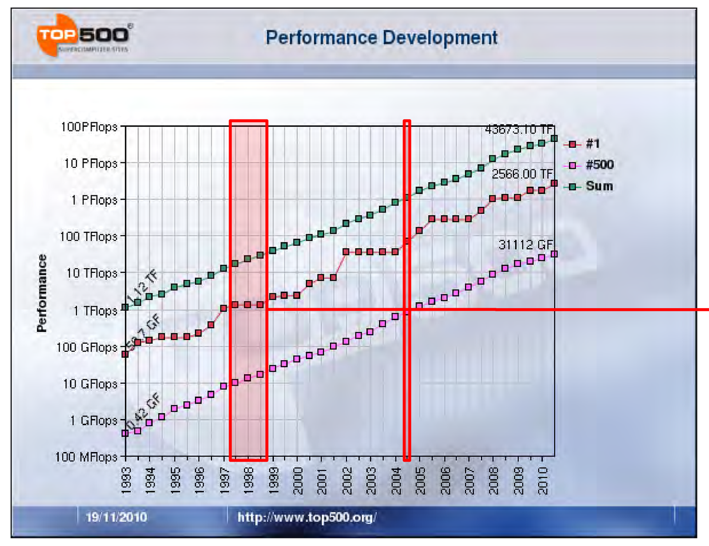


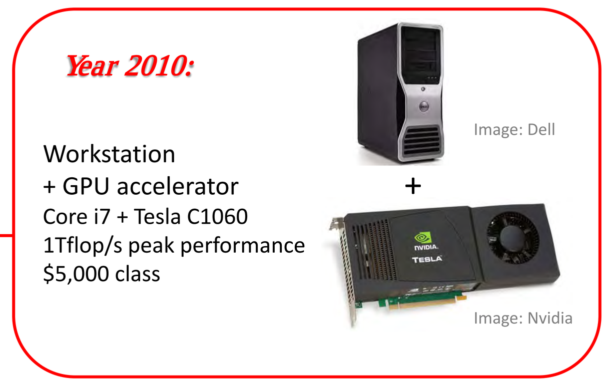
Active Role of Distribution System in Smart Grid

*Original figure by Andrew Hsu (EESG)

❖ Advances in High Performance Computing

- ‘2010, a **desktop workstation**’s peak performance comparable to:
  - **No. 1** fastest supercomputer in 1999;
  - **No. 500** fastest supercomputer in 2004.





- Trend in Parallelism
  - **NO** free speedup anymore, parallel program model required
  - Programmability & performance trade off
  - Specified application + Architecture optimized programming

❖ High Performance Computing Enabled Solution for Power System

- Monte Carlo simulation as an initial case:
  - “Golden standard” for probabilistic power flow
  - ***Embarrassingly Parallelizable*** on modern computing platform
  - Extensible to contingency analysis, steady state time-series…

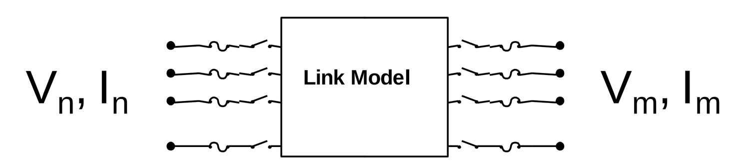
An Affordable Supercomputing Center for Distribution Substation

Methods

❖ Distribution Power Flow Model

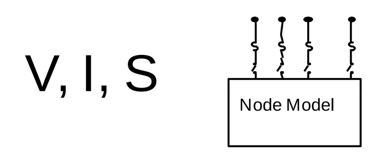
- Three phase unbalanced model example

Two terminal link model:

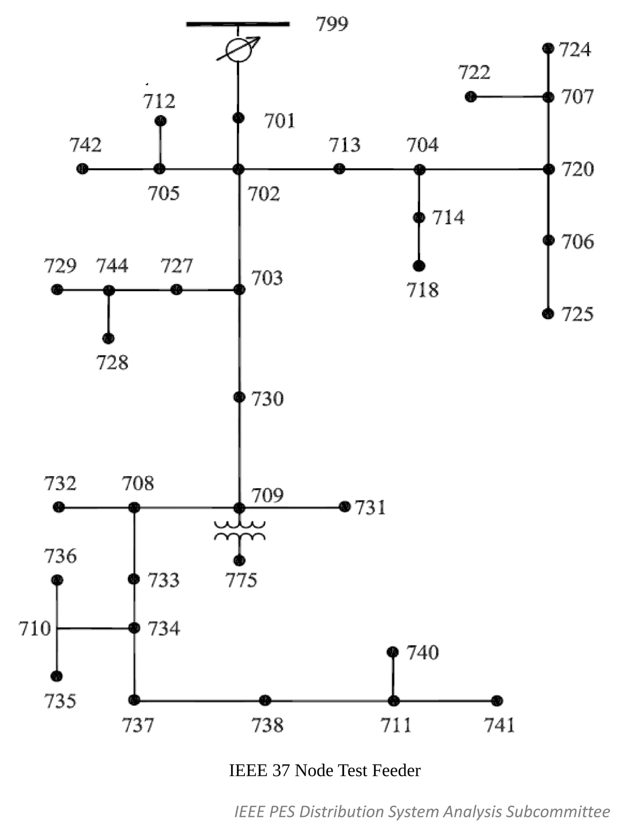


$$[I_{abc}]_n = [c]\cdot[V_{abc}]_m + [d]\cdot[I_{abc}]_m$$
$$[V_{abc}]_m = [A]\cdot[V_{abc}]_n - [B]\cdot[I_{abc}]_m$$

One terminal node model:

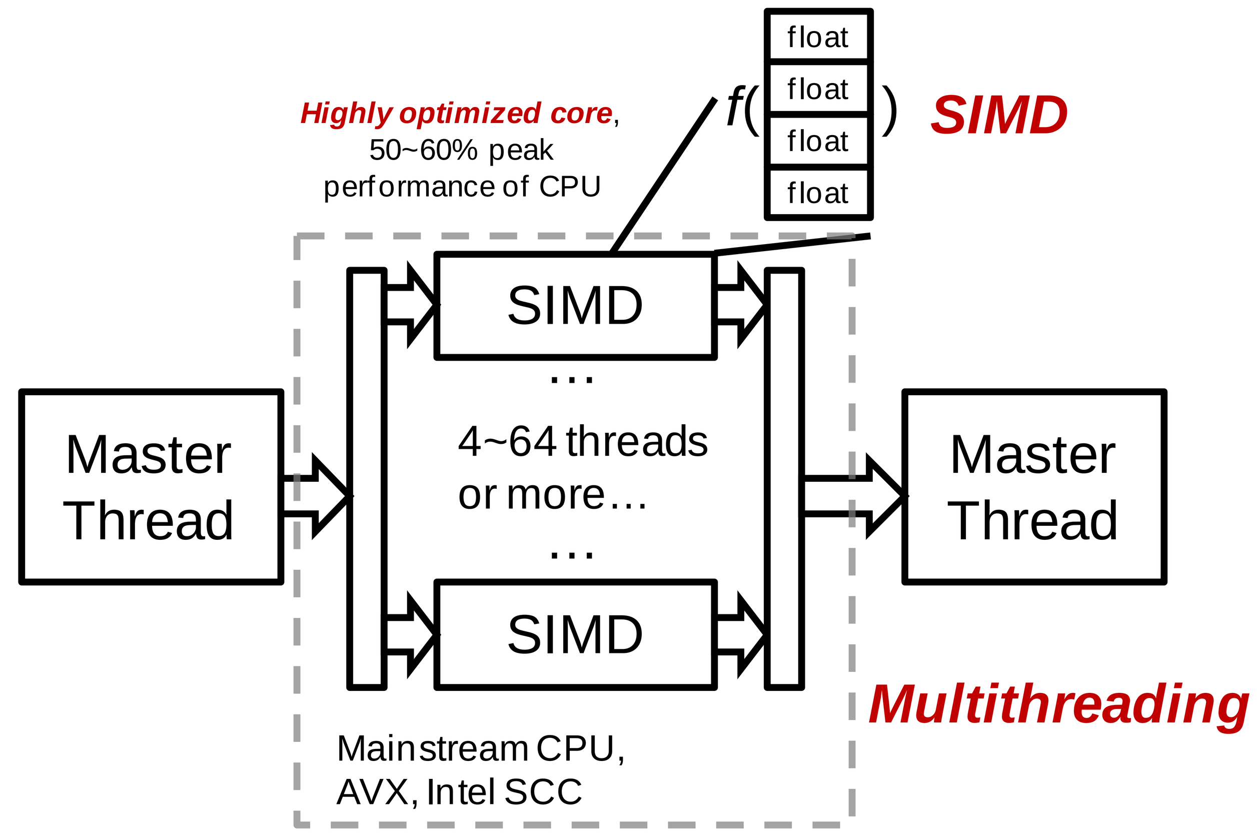


$$[S_{abc}] = [V_{abc}]\cdot[I_{abc}]^*$$



- Forward backward sweep: small size complex ***Matrix-Vector Mult***

❖ Massive Parallel Framework on Multi-Core + SIMD



- Available multi-core / many-core platform:
  - Intel Kentsfield / Nehalem / SandyBridge, SSE and AVX.
  - Intel Single Chip Cloud Computing, 48 cores on chip.

❖ Optimizing / tuning techniques for computation core

- Simple array storage instead of complex data structure.
- Optimized for architecture: “cache”, “superscalar,” “out of order”.
- Keep computation running at register level.

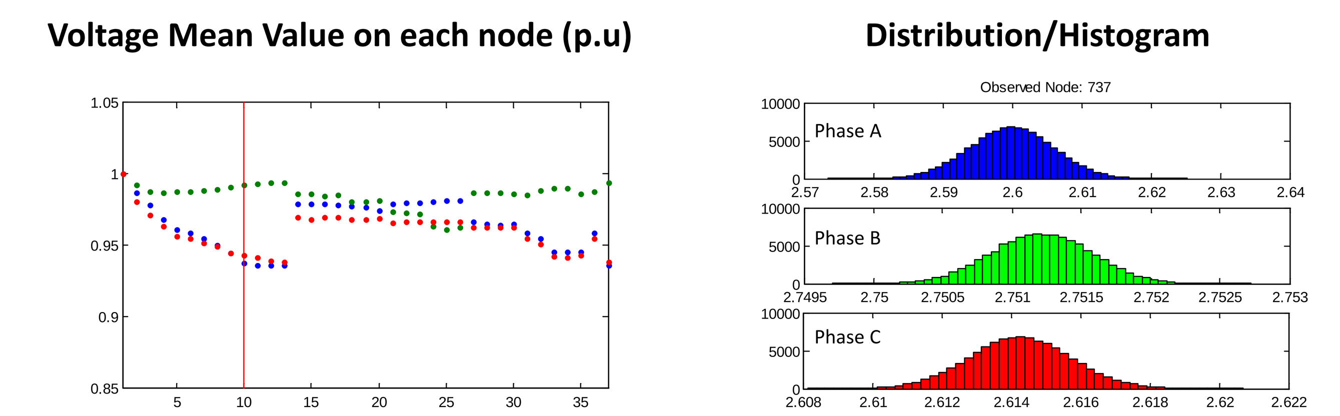
Squeezing Computation Power out of the Computer Architecture.

Push Performance to the Hardware Peak.

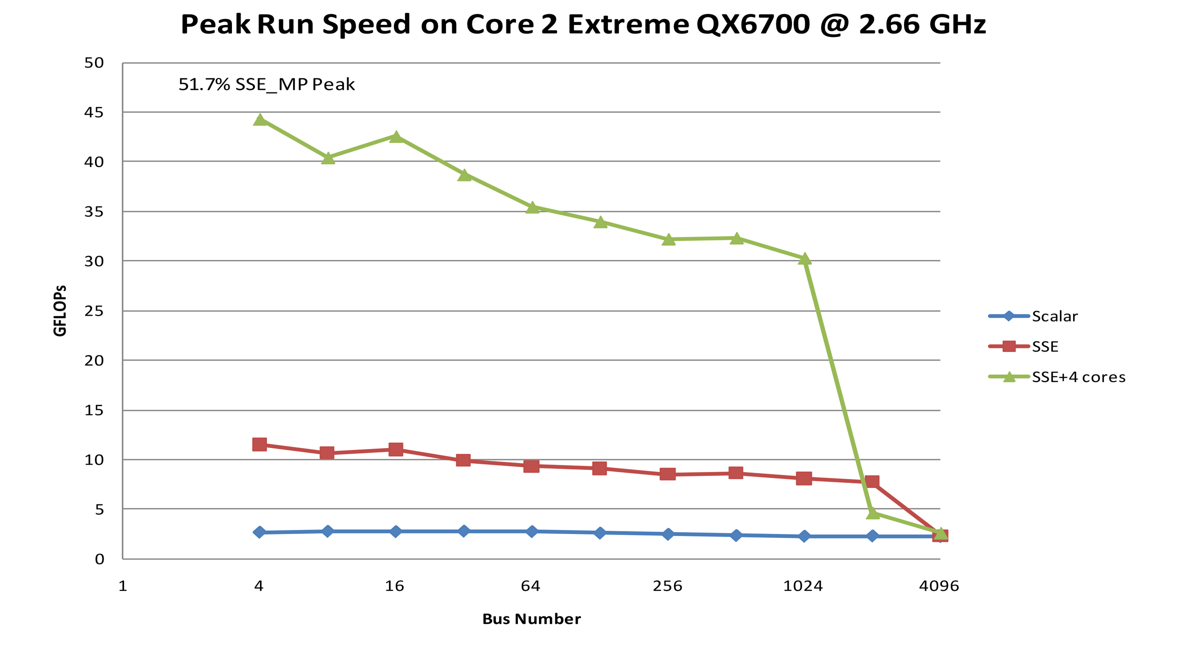
Software & Preliminary Results

❖ Software

- Core program + Intel MKL + MATLAB Interactive Interface:



❖ Performance Result



Theoretical Peak Performance in Intel Specs: 85 GFLOPs

- Blue line (optimized single thread) : 300x faster than MATLAB, 3x faster than C++.
- Speed translates to runtime:

Optimized Performance on Core 2 Extreme @ 2.66GHz

Problem Size	Approx. flops	Approx. Time
IEEE37: one iteration	12 Kilo	~ 0.3 us
IEEE37: one power flow (~5 Iterations)	60 Kilo	~ 1.5 us
IEEE37: 1 million power flow	60 Giga	~ < 2 seconds
IEEE123: 1 million power flow	200 Giga	~ < 10 seconds

Conclusions & Future Work

❖ Program optimization / parallelization:

- 12,000x faster than MATLAB, 120x faster than C++.
- Enable fast computation of large amount of power flow.

❖ Performance can be further increased on new platform:

- Intel SCC (48 cores on chip), AVX (8 float data per op)
- GPU: small, less powerful but many more cores.

❖ Applications of fast distribution power flow solver:

- Fast time series solution; smart relay co-ordination, statistic analysis…

Electric Energy Systems Group SPIRAL Electrical & Computer ENGINEERING

Robust State-Estimation Procedure using a Least Trimmed Squares Pre-processor

Yang Weng, Rohit Negi, Zhijian Liu and Marija Ilić

Carnegie Mellon University

Motivation

- **Based on real-time measurements, Static State Estimation serves as the foundation for monitoring and controlling the power grid.**

❖ *Classical method:* The popular weighted least squares(WLS) with largest normalized residual removed, gives satisfactory performance when dealing with single or multiple uncorrelated bad data.

❖ *Problem:* When the bad data are correlated or bounded, this estimator has poor performance in detecting bad data.

❖ *New approach:* Using Robust Estimator to detect/remove bad data.

Preliminaries of State Estimation

- **Goal:** To determine the most likely state of the system based on the quantities that are measured.[1]
- **Model:** $z = Hx + e$
  - H: Measurement Jacobian
  - State(x): Voltage magnitudes and phase angles

$$\left(|V_{i_1}|, |V_{i_2}|, \dots, |V_{i_j}|, \delta_{i_1}, \delta_{i_2}, \dots, \delta_{i_j}\right)$$

  - Measurements(z) and noise(e):

$$P_i = f_P\left(|V_{i_1}|, |V_{i_2}|, \dots, |V_{i_j}|, \delta_{i_1}, \delta_{i_2}, \dots, \delta_{i_j}\right),$$

$$Q_i = f_Q\left(|V_{i_1}|, |V_{i_2}|, \dots, |V_{i_j}|, \delta_{i_1}, \delta_{i_2}, \dots, \delta_{i_j}\right), \qquad i_1, i_2, \dots, i_j \text{ are nodes connected to node } i$$

$$\rightarrow \begin{bmatrix} P_1 \\ P_2 \\ \vdots \\ P_N \end{bmatrix} = \begin{bmatrix} \sum_{n=2}^{N} |Y_{1n}| & -|Y_{12}| & \cdots & -|Y_{1N}| \\ -|Y_{21}| & \sum_{n=1,\neq 2}^{N} |Y_{2n}| & \cdots & -|Y_{2N}| \\ \vdots & \vdots & \ddots & \vdots \\ -|Y_{N1}| & -|Y_{N2}| & \cdots & \sum_{n=1}^{N-1} |Y_{Nn}| \end{bmatrix} \begin{bmatrix} \delta_1 \\ \delta_2 \\ \vdots \\ \delta_N \end{bmatrix}$$

$$\tilde{P}_i = P_i + n_{P_i}, \; \tilde{Q}_i = Q_i + n_{Q_i}, \; |\tilde{V}_i| = |V_i| + n_{|V_i|}, \; \tilde{\delta}_i = \delta_i + n_{\delta_i}, \qquad i = 1, 2, \cdots$$

$$n_{P_i} \sim N\left(0, \sigma_{n_P}^2\right), \; n_{Q_i} \sim N\left(0, \sigma_{n_Q}^2\right), \; n_{|V_i|} \sim N\left(0, \sigma_{|V|}^2\right), \; n_{\delta_i} \sim N\left(0, \sigma_{n_\delta}^2\right) \qquad \text{i.i.d.}$$

- Classical Method for state estimation
  1. Detection: Chi-square test to detect *Bad data* $L(\hat{x}) = \|r\|_2^2$ follows a $\chi^2(v)$ distribution *with v = m-n, and r is the residual.* $r = z - H\hat{x}$
  2. Bad date remover: Largest normalized residual
  3. State Estimation: $\hat{x} = (H^T R^{-1} H)^{-1} H^T R^{-1} z$

Example

- **IEEE 3 bus**

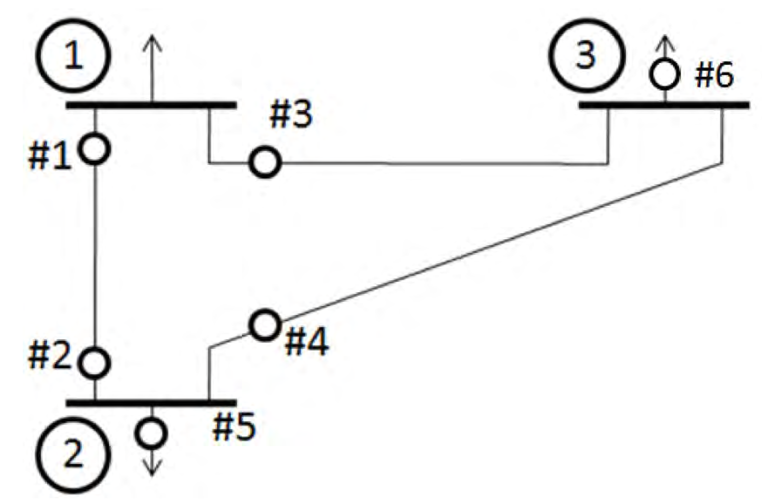


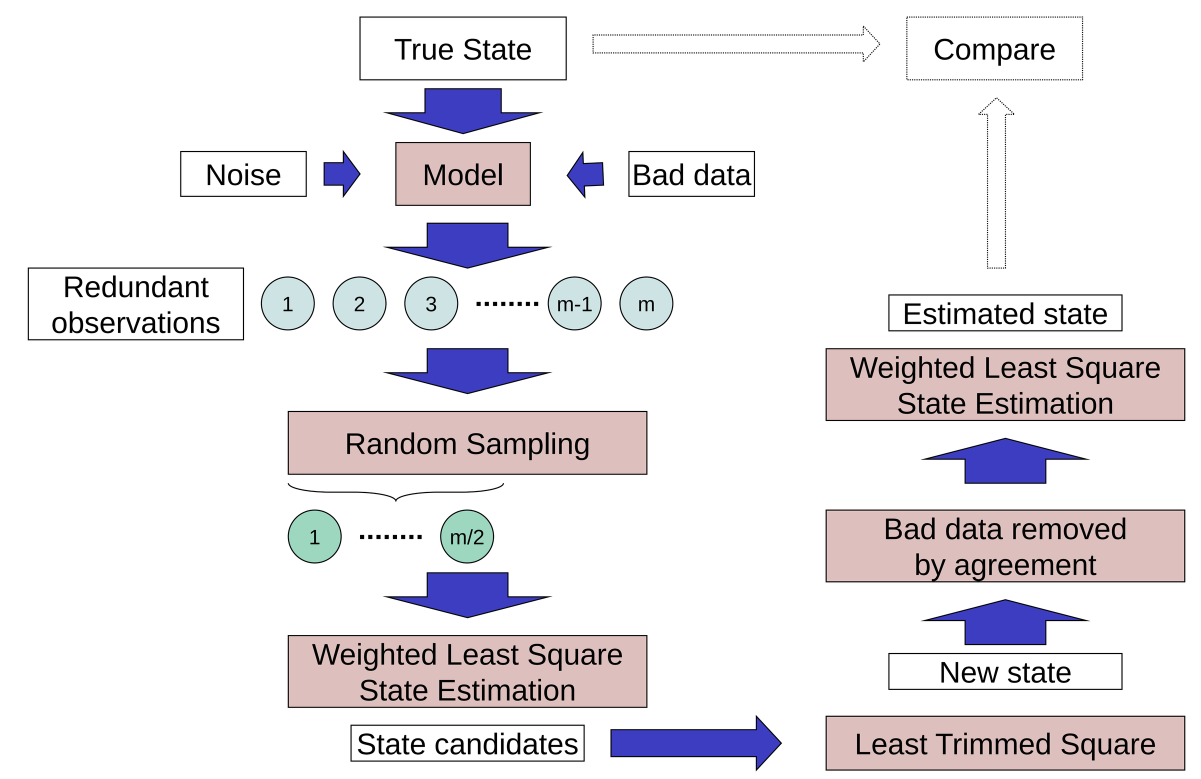
TABLE I
RESIDUALS FOR 3-BUS SYSTEM

Meas.#	W_{ii}	γ_{Ni}:1^{st}	γ_{Ni}:2^{nd}	γ_{Ni}:3^{rd}
1	0.90	3.42	2.90	1.54
2	0.90	-3.42	-2.90	-1.54
3	0.36	3.27	2.11	-2.39
4	0.96	8.32	—-	—-
5	0.74	5.70	6.75	—-
6	0.14	6.06	3.40	-2.39

- **Reference**
  - [1] A. Abur and A. G. Exposito, "Power System State Estimation: Theory and Implementation." Marcel Dekker Inc, 2004.
  - [2] A. Monticelli, State Estimation in Electric Power Systems, A Generalized Approach., 1999.
  - [3] S. Gastoni, G. P. Granelli, and M. Montagna., "Robust state estimation procedure based on the maximum agreement between measurements." IEEE Trans. Power Syst., vol. 19, no. 4, pp. 2038–2043, nov 2004.

New Approach

- LTS estimator as a pre-processor to detect bad data.
- A subsequent post-processor is employed to eliminate bad data and re-estimate the state.



•Step.1.Random Sampling of measurements

•Repeatedly select sample sets of m/2 measurements, for which the state remains observable.

•For each selected sample set, estimate the sate by WLS.

•Step.2.Least Trimmed Squares (LTS)

•Find the state candidate having the least sum of trimmed squares, among all candidates in step 1.

•Step.3.Bad Data Removal by agreement [3]

•Based on the residual generated in step 2, eliminate the data beyond a certain threshold.

•Step.4.Re-estimation

•Estimate the state by WLS, using the remaining (good) data.

Numerical Result

- **Simulation for IEEE 39 bus**
  - The state: 39 voltage magnitudes and 39 phase angles
  - The measurement:
    - Voltage magnitudes
    - Directed phase angle measurements
    - Active and reactive power measurements on the lines
    - Power injection at each bus
  - 1000 random sample sets of m/2 measurements

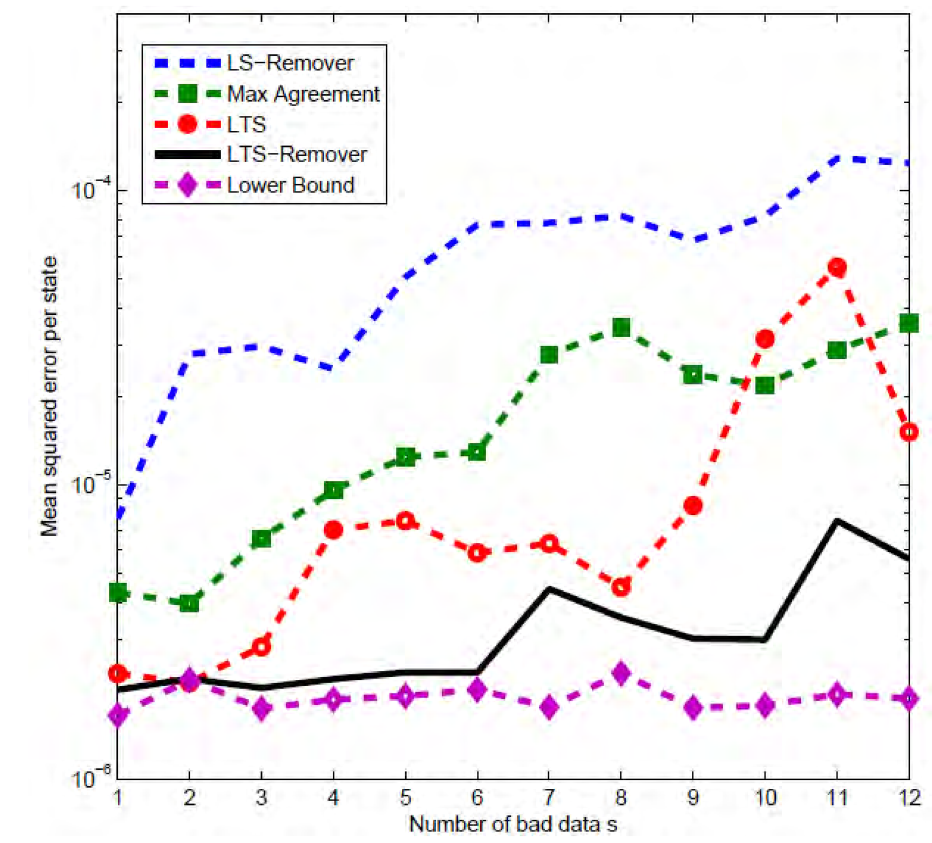


TABLE II
COMPUTATION TIME

Power grid	State Computation Time
39 bus	0.1923s

$$\varepsilon_{state} = \frac{1}{n}\left\{\sum_{l=1}^{n/2} E\left\|V_{l,est} - V_{l,true}\right\|_2^2 + \sum_{l=1}^{n/2} E\left\|\delta_{l,est} - \delta_{l,true}\right\|_2^2\right\}$$

A lower bound is also computed by assuming that an oracle provides WLS with the locations of the bad data.

Figure. Performance comparison for the 39 bus case.

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Greedy PMU Placement Algorithms for Power System State Estimation

Qiao Li, Rohit Negi and Marija Ilić

Motivation

- The PMUs currently deployed can not achieve full system observability
- Currently, PMU data are utilized to improve traditional state estimation results [1]
- *Problem*: How to place a small number of PMUs to *minimize state estimation error?*

PMU Augmented State Estimation

- Measurement model

Traditional measurement model	PMU measurement model
$\boldsymbol{z} = H\boldsymbol{x} + \boldsymbol{n}$	$\tilde{z}_i = \boldsymbol{e}_i^T \boldsymbol{x} + \tilde{n}_i, \quad \forall i \in S$
$\boldsymbol{z}$: real power flow measurements H : measurement Jacobian matrix $\boldsymbol{x}$: phasor angles $\boldsymbol{n}$: measurement noise $\sim \mathcal{N}(\boldsymbol{0}, W^{-1})$	S : PMU buses $\tilde{z}_i$: voltage angle measurement $\boldsymbol{e}_i = (0, 0, \ldots, 0, \underbrace{1}_{i\text{th position}}, 0, \ldots, 0)^T$ $\tilde{n}_i$: PMU measurement noise $\sim \mathcal{N}(0, \tilde{\sigma}_i)$

Combined together: $\begin{pmatrix} \boldsymbol{z} \\ \tilde{\boldsymbol{z}} \end{pmatrix} = \begin{pmatrix} H \\ \tilde{H} \end{pmatrix} \boldsymbol{x} + \begin{pmatrix} \boldsymbol{n} \\ \tilde{\boldsymbol{n}} \end{pmatrix}$

- PMU augmented estimator

Direct Estimator: $\hat{\boldsymbol{x}}_S = \tilde{\boldsymbol{z}}_S$ (set PMU bus voltage angles as measurements)

$H = (H_S \quad H_{\bar{S}})$ $\quad \hat{\boldsymbol{x}}_{\bar{S}} = (H_{\bar{S}}^T W H_{\bar{S}})^{-1} H_{\bar{S}}^T W (\boldsymbol{z} - H_S \tilde{\boldsymbol{z}}_S)$

(use traditional state estimator on non-PMU buses)

Theorem 1 *(Equivalent Estimators)*: When $\max_{i \in S} \tilde{\sigma}_i \to 0$, the WLS estimator converges to the direct estimator, with error covaraince matrix

$$\hat{\Sigma}(S) = \begin{pmatrix} (H_{\bar{S}}^T W H_{\bar{S}})^{-1} & 0 \\ 0 & 0 \end{pmatrix}$$

error by traditional state estimator

Problem Formulation

Choose PMU buses $S^\star$ such that $S^\star \in \arg\min_{|S| \le K} \hat{\Sigma}(S)$

(matrix objective function, can only solve for *maximal* solutions)

Any good criterion for choosing a maximal solution? Choose scalar functions of $\hat{\Sigma}(S)$ [2]

Related optimality	"A-optimality"	"D-optimality"
Objective function	$\Psi_A(S) = \mathrm{trace}(H^T W H)^{-1} - \mathrm{trace}(H_{\bar{S}}^T W H_{\bar{S}})^{-1}$	$\Psi_D(S) = \log\det(H_{\bar{S}}^T W H_{\bar{S}}) - \log\det(H^T W H)$
Interpretation	***reduction in total error variance***	***reduction in entropy*** (approximately)

Greedy PMU Placement

Algorithm 1 Greedy
Initialize: $S = \emptyset$;
for $k = 1$ to K **do**
$\quad s(k) = \arg\max_{s \notin S} F(S \cup \{s\}) - F(S)$;
$\quad S = S \cup \{s(k)\}$
end for
return S

$F(S)$ can be $\Psi_A(S)$ or $\Psi_D(S)$

Performance guarantee?

Submodularity Guarantee

- Definition of submodularity

A set function $F : \mathcal{S} \to \mathbb{R}$ is *submodular* if
- $F(\emptyset) = 0$;
- $F(S \cup T) + F(S \cap T) \le F(S) + F(T)$ for all sets S and T in $\mathcal{S}$

- Well-known performance guarantee [3]

For a nondecreasing submodular function $F(S)$,

$$F(S_g(K)) \ge (1 - \frac{1}{e}) F(S^\star(K))$$

greedy solution $\quad$ optimal solution

In words, for submodular functions, greedy algorithm achieves at least 63% optimality!

Main Results

- "A-optimality" (total variance reduction)

Theorem 2: $\Psi_A(S)$ is nondecreasing, and *submodular* if for any $S \subseteq T$, and any column $\boldsymbol{h}$ of H not in T

$$\frac{1 + \|(H_S^T W H_S)^{-1} H_S^T W \boldsymbol{h}\|^2}{\|P_{H_S^\perp} \boldsymbol{h}\|^2} \le \frac{1 + \|(H_T^T W H_T)^{-1} H_T^T W \boldsymbol{h}\|^2}{\|P_{H_T^\perp} \boldsymbol{h}\|^2}$$

projection onto $H_{S^\perp}$ $\quad$ projection coefficients onto H_S

Assumption holds when the columns of H are nearly orthogonal, which is true for typical (branch) real power flow measurements.

Essentially, the greedy algorithm achieves at least 63% optimal total error variance reduction!

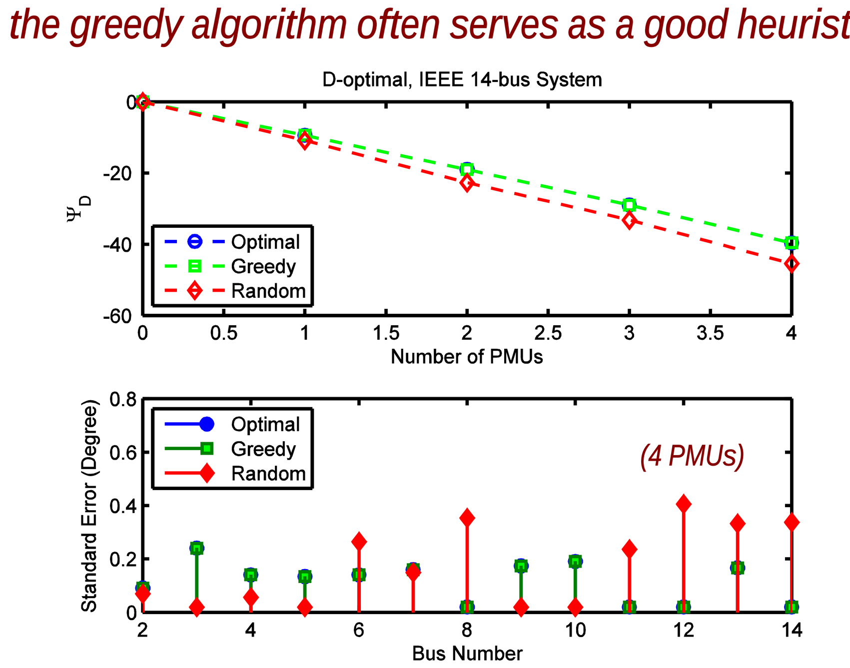
- "D-optimality" (entropy reduction)

Theorem 3: $\Psi_D(S)$ is *submodular*.

(but performance hard to guarantee since the function may be decreasing)

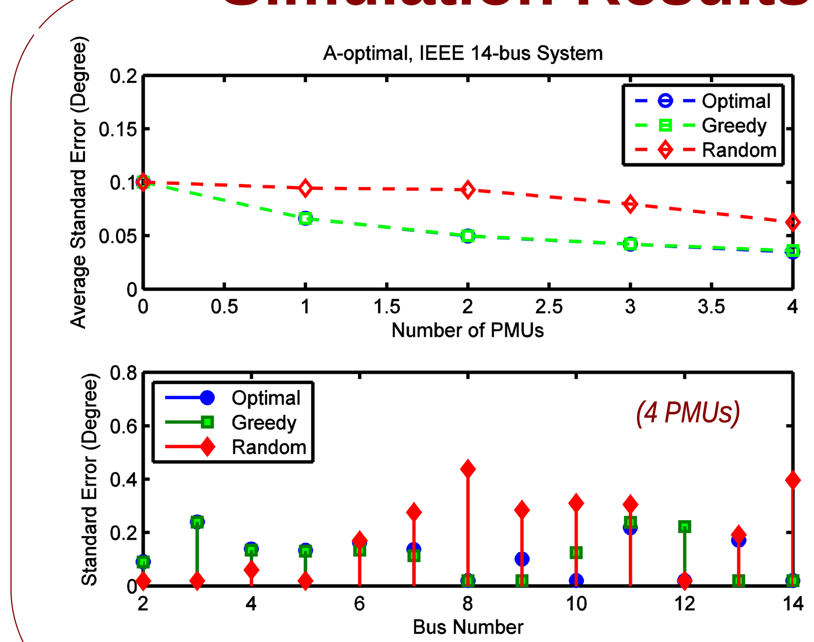
In the literature, the greedy algorithm often serves as a good heuristic.

Example:

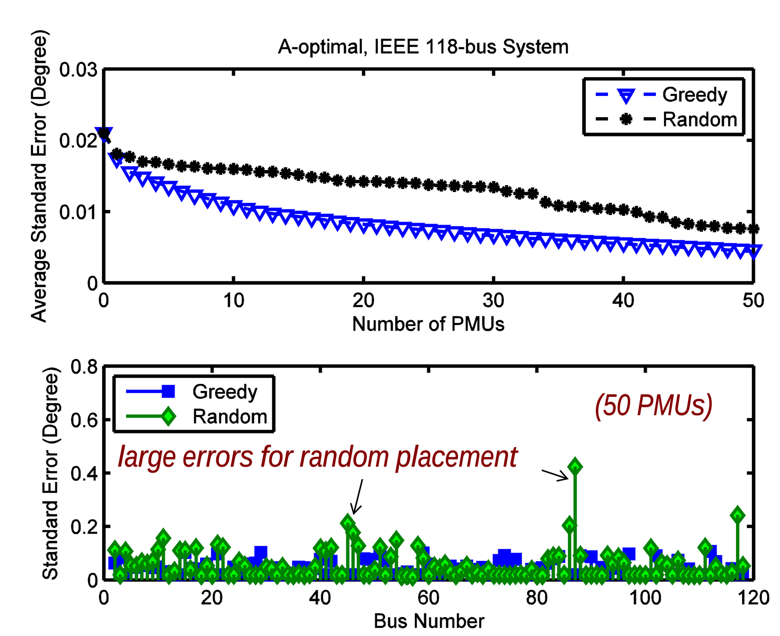


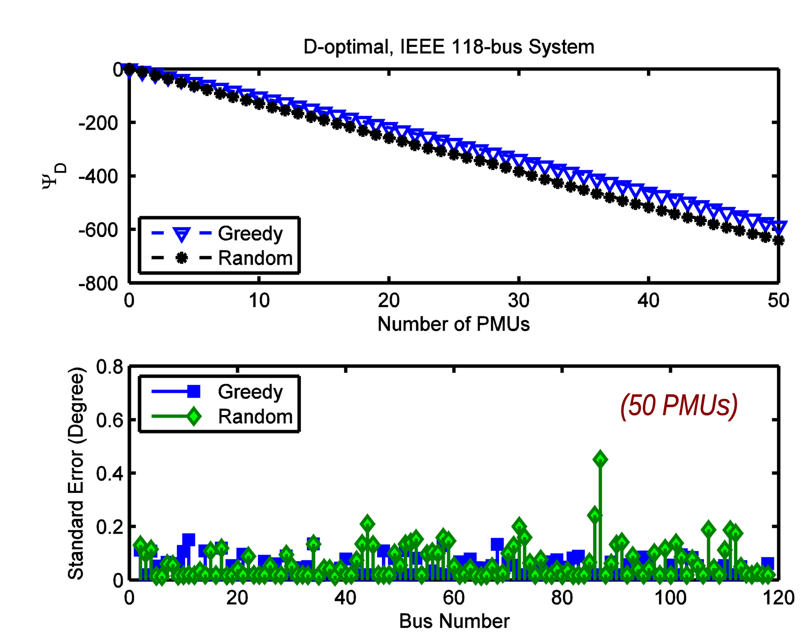
The same as optimal!

Simulation Results



Almost the same as optimal!





Most errors are small for the greedy algorithm.

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